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Agglomeration Economies, Firm-level Efficiency and Productivity Growth: Empirical Evidence from Indonesia

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material, which has been accepted for the award of any other degree or diploma in any university.

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Wahyu Widodo

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List of Abbreviations and Acronyms

ADB	Asian Development Bank
BPIS	Agency for Strategic Industry *(Badan Pengelola Industri Strategis – BPIS)*
BPS	Statistics Indonesia *(Badan Pusat Statistik)*
CBD	Central business district
CR4	Industrial concentration ratio
CRTS	Constant returns to scale
DEA	Data envelopment analysis
ECM	Error component model
EGI	Ellison-Glaeser Index
EIA	Energy Information Administration
FDI	Foreign direct investment
FEM	Fixed effects model
FGLS	Feasible generalized least square
Gaikindo	The Association of Indonesian Automotive Industries
GBHN	Blueprint of medium term development framework (*Garis-garis Besar Haluan Negara)*
GDP	Gross Domestic Product
GLS	Generalized least square
GMI	Gibbs-Martin Index
GMM	Generalized method of moments
HHI	Hirchman-Herfindahl Index
HPH	Special rights for forest resource exploration *(Hak Pengusahaan Hutan)*
IBRD	International Bank for Reconstruction and Development
IGGI	Inter Governmental Groups on Indonesia
ILO	International Labour Organization
IMF	International Monetary Fund
IRTS	Increasing returns to scale
ISIC	International Standard Industrial Classification
KAPET	Integrated Economic Development Zone (*Kawasan Pengembangan Ekonomi Terpadu)*
KBLI	Indonesian Standard Industrial Classification *(Klasifikasi Baku Lapangan*

	Usaha Indonesia)
KEK	Special Economic Zone *(Kawasan Ekonomi Khusus)*
KPPU	Commission for the Supervision of Business Competition *(Komisi Pengawas Persaingan Usaha)*
LOI	Letter of Intent
LP	Linear program
LPG	Liquid petroleum gas
LQ	Location quotient
MAR	Marshall-Arrow-Romer
ML	Maximum likelihood
MNCs	Multinational corporations
n.e.c	Not elsewhere classified
NCT	Neo-Classical Theory
NEG	New Economic Geography
NIEs	Newly Industrialized Economies
NTT	New Trade Theory
OECD	Organization for Economic Co-operation Development
OLS	Ordinary least square
PLN	State Electricity Company *(Perusahaan Listrik Negara)*
PSID	Firm identity codes
R&D	Research and development
REM	Random effects model
RPJMN	National Medium Term Development Plan (*Rencana Pembangunan Jangkan Menengah Nasional)*
RPJPN	National Long Term Development Plan *(Rencana Pembangunan Jangka Panjang Nasional)*
SCP	Structure–conduct–performance
SFA	Stochastic frontier approach
SMEs	Small Medium Enterprises
SOEs	State Owned Enterprises
SPF	Stochastic Production Frontier
TE	Technical efficiency
TFP	Total Factor Productivity

VCE	Variance-covariance matrix of estimator
VRS	Variable returns to scale
WB	World Bank
WLS	Weighted least square
WPI	Wholesale price index

Abstract

This thesis examines the effect of agglomeration economies on firm-level efficiency and productivity growth in Indonesian manufacturing industries. Agglomeration economies are generally recognized as location-specific economies. Though agglomeration has become a main characteristic of industrial development in Indonesia, determining its effects on firm-level efficiency and productivity growth remains a challenge and, further, the number of empirical studies of these effects is limited.

The basic hypothesis is that agglomeration economies have positive effects on firm-level efficiency and productivity growth. The benefits of agglomeration are acquired first and mainly accrue to the agglomerated firms in the form of externalities that strengthen efficiency and productivity. The empirical analysis of this thesis is focused on the key features of agglomeration economies, namely Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity), and Porter's externalities (or competition). A set of firm and industry characteristics that are considered to influence firm-level efficiency and productivity growth are also fitted in the analysis. These variables include age, size, market concentration, and firm location for both urban region and industrial complexes.

While considering the specific characteristics of the manufacturing industries and regions, this thesis uses the stochastic production frontier (SPF) approach to examine the effect of agglomeration economies on firms' productive efficiency levels. Subsequently, the Färe-Primont productivity index is employed to measure productivity growth and its decomposition, and econometric estimation using panel data is applied to investigate the effect of agglomeration economies on productivity growth.

Empirical results show evidence of positive specialization effects and negative diversity effects, indicating that specialization is more favourable than diversity for stimulating firm-level efficiency. It confirms that inter-firm knowledge spillovers are transmitted in the regions that consist of homogeneous industries. Further, the positive effects of high levels of competition and domination by small firms suggest that Porter's externalities stimulate firm-level efficiency. Competition drives firms to innovate, which in turn accelerates efficiency and productivity growth.

In terms of firm location, both urban regions and industrial complexes have positive effects, indicating that firms located in both areas experience higher efficiency. This confirms that an adequate business environment and infrastructure play a crucial role in improving firm-level efficiency. Also, both firm age and firm size are found to have a positive effect upon firm-level efficiency, suggesting that older firms tend to have higher efficiency than younger firms and larger firms tend to be more productive than smaller firms.

The decomposition analysis finds that technical change is the main source of productivity growth, while scale efficiency change and technical efficiency change contribute less to productivity growth. However, the year-on-year trend shows that productivity growth fluctuates. Among industries, the motor vehicle industry most frequently achieves the highest productivity growth level. Finally, testing the effects of agglomeration economies on productivity growth shows that specialization is found to be more conducive than diversity to improving productivity growth.

This study finds that agglomeration contributes significantly to firm-level efficiency and productivity growth. Therefore, the Indonesian government should consider prioritizing agglomeration in formulating its spatial industrial policy, specifically by focusing on facilitating the agglomeration process and improving the competitiveness of agglomeration areas. As the presence of industrial complexes has a positive effect on firm-level efficiency, the government should also continue to develop the number of industrial complexes required to promote industrial development, as well as special economic zones and integrated economic development zones. Similarly, because urban regions are found to promote firms' productivity growth, the government should strive to ensure sound and ever-improving business environments in these areas.

Key words: agglomeration economies, externalities, industrial structure, technical efficiency, productivity growth and stochastic production frontier

JEL classification: L25; L60; R12

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Chapter 1
Introduction

1.1. Background of the Research

The fact that economic activities are concentrated in certain regions has become a common phenomenon in both developed and developing countries. Some of the most popular examples are the high-tech industry in the Silicon Valley or the auto industry in Detroit (Glaeser et al. 1992). In a spatial perspective, this feature is often referred to as agglomeration, and it is frequently applied to the spatial distribution of specific industries (Brulhart 1998). The benefits from agglomeration are known as agglomeration economies (Rosenthal and Strange 2003) or location-specific economies, which are independent of a single firm, but accrue to all of the firms located in the same area (McCann 2008). The tendency of firms and peoples to be concentrated in a particular space is actually motivated by rational economic reasons. Agglomeration economies are understood to provide economic reasons for the clustering of economic activities as well as the tendency of the geographic concentration of firms to persist over time (Andersoon and Lööf 2011).

The notion that agglomeration economies encourage spatial concentration has led to a good deal of research on the relation between agglomeration and productivity (Rosenthal and Strange 2004). The focus has been on whether agglomeration economies promote productivity growth. Glaeser et al. (1992) pioneered studies in this field, formulating the terminology “dynamic externalities” to explain how firms gain from external economies. The three types of dynamic externalities proposed by Glaeser et al. (1992) are Marshall-Arrow-Romer (MAR) externalities, Jacobs’ externalities, and Porter’s externalities, which are also referred to as specialization, diversity, and competition, respectively. The core of the distinction among these concepts lies in the question of whether knowledge spillovers come from within the industry or from other industries, and the role of competition in influencing knowledge spillovers.

The MAR theory of spillovers deals with spillovers within an industry. Firms benefit from location and physical proximity through intra-firm exchanges of knowledge and information, reduced costs from labour pooling, and input sharing. The accumulated knowledge and experience of one firm will be transmitted to other firms without appropriate compensation. Indeed, industries that are regionally specialized and gain the most from knowledge spillovers within an industry are believed to grow faster (Glaeser et al. 1992).

In contrast, Jacobs' (1969) theory of spillovers emphasizes the role of diversity or variety in industries for promoting growth. In a diversified area, the interchange of ideas and knowledge between firms is more frequent, so the variety of industries within a region stimulates knowledge externalities, which in turn result in local industrial growth. As a result, industries located in regions that are highly diversified have a greater chance to grow faster, relative to industries located in more specialized regions. Accordingly, regions with a diversified economic structure should also grow faster than specialized areas (Quigley 1998).

Finally, in terms of competition, Jacobs (1969) and Porter (1990) agree that local competition is more conducive to industrial growth, in contrast with MAR, who believe that local monopolies are more appropriate. Porter's model emphasizes the idea that local competition forces firms to improve their ideas and to accelerate the imitation process. A high level of competition provides incentives for firms to innovate through higher allocations of R&D spending (Combes 2000). The pressure to produce creative innovation is much greater in competitive regions, which then leads to improved technological progress, and hence productivity growth. By contrast, MAR believe that local monopolies are more appropriate accelerators of growth, because firms will internalize the externalities. Under low levels of competition, firms can monopolize their ideas to accelerate the innovation process without any significant threats from competitors, especially threats against imitation and duplication of their ideas. This circumstance leads to industrial growth (Glaeser et al. 1992).

These insights about external economies have led empirical studies on agglomeration economies and productivity growth to focus on the disagreement between the two main theories of external economies, namely specialization (or MAR externalities) and diversity (or Jacobs' externalities). However, the two theories are not necessarily mutually exclusive or always contradictory (Beaudry and Schiffauerova 2009). The main concern in the empirical literature is whether specialization or diversity is better at promoting productivity growth, with findings showing mixed results regarding the effect of agglomeration economies on growth.

Most of early studies consider the effect of agglomeration economies upon spatial growth using aggregate-level data. Among these studies are, for example, Glaeser et al. (1992), Henderson et al. (1995), Ellison and Glaeser (1997), Combes (2000), Duranton and Puga (2004), and Cingano and Schivardi (2004). Since productivity contributes importantly to economic growth and agglomeration is essentially a micro-behaviour, the objective of the research in this field has shifted to examining the effect of agglomeration economies on firm productivity, using firm-level data rather than aggregated data.

Henderson's seminal work (2003) is one of the first empirical studies of the effects of agglomeration economies on firm-level productivity growth. Many studies similar to Henderson (2003) examine other cases and regions. Positive effects of MAR externalities on productivity are found in Henderson et al. (2001), Henderson (2003), Duranton and Puga (2001), Lee et al. (2010), Kuncoro (2009), Graham and Kim (2008), and Anderson and Lööf (2011), while negative effects are found in Batisse (2002). Positive effects of Jacobs' externalities on productivity are mentioned in Henderson et al. (2001) and Capello (2002), while negative effects are found in Frenken et al. (2005).

Regarding variations in the empirical findings on the effects of agglomeration economies on productivity growth, Beaudry and Schiffauerova (2009) state that outcomes may depend on the method used to measure agglomeration variables, the region of study, which industries are included in the study, and the aggregation level of region. Empirically, differences in findings also depend on the research design, methodology, data availability, estimation approach, and construction of the agglomeration economy variables.

The variations and differences in the empirical findings indicate that the relationship between agglomeration economies and productivity growth remains an empirically fruitful area of research, providing space for further research to explore the nature of agglomeration economies and firm productivity. Moreover, Rosenthal and Strange (2004) emphasize our knowledge about agglomeration economies is limited, so that the debate about industrial and geographic concentration and the scope of agglomeration economies continues.

Empirical analysis of the relation between agglomeration economies and productivity growth in Indonesia has been very limited. Most previous studies use real labour productivity growth as the main measure instead of using total factor productivity (TFP) growth, and the analysis has focused only on the productivity measure, with no concern for its sources. The use of TFP growth allows us to glean broader insights about the effects of agglomeration economies on productivity. Previous studies are also limited to a selection of sub-sector industries, which are not compared with the aggregate manufacturing industry. This leads to a loss of important information on the nature of agglomeration economies in the aggregated and in each sub-sector industry. Since agglomeration is a main characteristic of industrial development in Indonesia (Hill 1990b; Hill et al. 2008), a comprehensive analysis is needed to assist the government in formulating national industrial policy.

This thesis attempts to enrich the research on agglomeration economies and productivity growth by carrying out a level of analysis that has not been conducted in previous studies, particularly in the case of Indonesia. Three approaches are employed to achieve the goals of the study. First, a stochastic production frontier (SPF) is applied to examine the effect of agglomeration economies on firm productive efficiency. Second, Färe-Primont productivity indexes are used to decompose total factor productivity growth and its sources. Finally an, econometric model using panel data is utilized to estimate the effect of agglomeration economies on productivity growth.

1.2. Research Objectives

The main objective of this thesis is to analyse the manner in which agglomeration economies contribute to productivity growth in the Indonesian manufacturing industry. The detailed objectives are as follows:

1. To examine the impact of agglomeration economies on firm-level productive efficiency in the Indonesian manufacturing industry.
2. To investigate the sources of total factor productivity (TFP) growth and to map the pattern of productivity by three-digit ISIC manufacturing industry.
3. To examine the effect of agglomeration economies on productivity growth in manufacturing industry in aggregate and by sub-sectors.
4. To recommend relevant policies related to the phenomena of agglomeration economies in Indonesia.

Agglomeration is an important key to the process of economic development in Indonesia. It facilitates economic growth, especially in modern manufacturing industries (World Bank 2012). Agglomeration is also a major characteristic of regional development, where economic activities tend to be concentrated in the centre of regional growth. Hill (1990b) and Hill et al. (2008), for example, provide one prominent analysis of this issue. The island of Java remains the centre of manufacturing activities, contributing 76.62 percent of total manufacturing output in 2009. More specifically, manufacturing production and activities tend to be concentrated in particular cities and their surrounding areas. Jakarta and the surrounding area is the largest region, with 48 percent of output, followed by Surabaya (12.4%), Bandung (3.7%), Semarang (3.2%), and Batam (3%). Firms choose to locate near large cities due to the availability of adequate infrastructure, proximity to markets, and better access to services. Centralized bureaucracy in the early stages of industrial development leads manufacturers to place their production-bases closer to the large provincial capitals.

The process of industrial agglomeration became more structured and dynamic after the release of Presidential Decree 41/1996 regarding the establishment of industrial complexes, which was then followed by government regulation of the development of special economic zones *(Kawasan Ekonomi Khusus – KEK)* and integrated economic development zones *(Kawasan Pengembangan Ekonomi Terpadu – KAPET)*. By providing special facilities and incentives, these policies allow for more concentrated industrial activities in specific areas. Finally, the decentralization policy announced in 1999, which led to rapid regional fragmentation, has made the industrial agglomeration process in Indonesia more complex and challenging.

1.3. Methods of Research

To achieve the research objectives, this thesis employs the stochastic production frontier (SPF) proposed by Battese and Coeli (1995), the Färe-Primont productivity index proposed by O'Donnell (2012), and an econometric model using a panel data framework. The stochastic production frontier is used to estimate the effects of agglomeration economies on firm-level productive efficiency. The Färe-Primont productivity index is used to compute and decompose total factor productivity (TFP) growth into various finer measurements including technical change, scale efficiency change, and technical efficiency change. In addition, an econometric model is used to estimate the effect of agglomeration economies on productivity growth, using both static and dynamic models.

In the stochastic production frontier, the agglomeration economies variables are included in the technical efficiency function, along with other variables understood to affect technical efficiency, namely firm age, size, market concentration, and two dummy variables representing industrial complexes and urban regions. The estimation is performed by aggregate manufacturing industry to see the general influence that agglomeration economies exert on firm-level technical efficiency.

In addition, in the Färe-Primont productivity index, a decomposition of total factor productivity growth is carried out for aggregate manufacturing industry and at the three-digit manufacturing level. The Färe-Primont productivity index proposed by O'Donnell (2012) is one of the most up-to-date approaches available, allowing the decomposition of productivity into finer components, unlike conventional productivity index measurements. This approach also ensures the multiplicatively complete index measurement required by an index decomposition method.[1] The possibility of decomposing productivity into broader components provides more extensive insight of productivity growth, both by aggregate industry and on the sub-sector level.

Finally, the econometric model using the panel data framework is run on the industry aggregate and sub-sectors. To enrich the analysis, both static and dynamic models are employed. Productivity growth, the main objective, is regressed against agglomeration economy variables and other variables representing firm and industry characteristics, as mentioned above.

1.4. Significance of the Research

This thesis contributes to the literature about agglomeration economies and productivity growth in Indonesia in several significant ways. Firstly, this study takes a new approach to estimating the effect of agglomeration economies on firm-level productive efficiency. In the Indonesian case, no previous study has used the stochastic production function to examine agglomeration economies. Generally,

[1] According to O'Donnell (2012), TFP index is said to be *multiplicatively complete* if aggregator functions, X(.) and Q(.), have all regularity properties of index number theory.

previous studies used conventional production function approaches, which assume full efficiency, complete capacity utilization and constant returns to scale.

Secondly, the use of the Färe-Primont productivity index proposed by O'Donnell (2012) allows the decomposition of productivity growth into finer components. Six components of productivity growth can be derived using this approach, unlike conventional methods such as the Divisia index or Malmquist productivity index that only decompose total factor productivity growth into three main sources: technical change, scale efficiency change, and technical efficiency change.[2] The Färe-Primont method also allows the identification of the industries that reach maximum productivity levels each year. Consequently, a more extensive analysis can be conducted using these decomposition results.

Thirdly, this study analyses the effect of agglomeration economies on productivity growth by aggregate manufacturing industry and by sub-sector, including 21 industries at the two-digit ISIC level. This enables more in-depth analysis, because each industry has a different structure and different characteristics. Previous studies in Indonesia only focus on specific industries. Linked analysis between aggregate industries and sub-sectors can also be conducted as a result of this study. This study uses total factor productivity growth to represent firm productivity, instead of real labour productivity, as is commonly used in previous studies. This provides a different perspective in examining the effects of agglomeration economies on firm productivity.

Finally, this thesis enriches the literature on the relationship between agglomeration economies and productivity growth, specifically in the Indonesian case, where there have been few previous empirical studies. Since agglomeration is a main characteristic of economic activities in the manufacturing industry, the results of a study in this field will offer important assistance to the government in formulating industrial development policy.

[2] The Färe-Primont productivity index proposed by O'Donnell (2010, 2012) can decompose the productivity change into six components, where one of the components may be the result of multiplying the other components. For the decomposition of productivity change using input-oriented approach, for example, the TFP growth can be decompose into: ΔTFPE – TFP efficiency change; ΔTFP* - technical efficiency change; ΔITE – technical efficiency change; ΔISE – scale efficiency change; ΔIME – mix efficiency change; and ΔISME – mix scale efficiency change. The letter I in each component means "input-oriented".

1.5. Structure of the Thesis

This thesis consists of eight chapters. Chapter 1 provides an introduction to the study. The research background, objectives, and significance of the study are presented. Chapter 2 discusses the industrial development process and policies since the early 1970s, when modern industrial development was implemented. General achievements, industrial development stages, policy maps, and challenges are discussed, specifically with regard to industrial development as it relates to the nature of agglomeration processes in Indonesia, such as spatial and regional concentrations.

Chapter 3 presents a review of the literature on agglomeration economies and productivity growth. The nature of agglomeration and its benefits are discussed, along with the way that agglomeration economies affect productivity and economic growth. The three main ideas regarding external economies and spillovers proposed by Marshall (1920), Jacobs (1969), and Porter (1990) are explored in this chapter. In addition, empirical evidence about agglomeration economies and productivity growth are summarized.

Chapter 4 provides an analytical framework to examine the impact of agglomeration economies on productivity in the Indonesian manufacturing industry. Three methods are briefly discussed, including the stochastic production frontier (SPF), Färe-Primont productivity index, and an econometric model using a panel data framework. Following Battese and Coelli (1995), the SPF is used to estimate the impact of agglomeration economies on productive efficiency levels. The Färe-Primont productivity index proposed by O'Donnell (2012) is employed to decompose productivity growth, and the econometric model is used to estimate the impact of agglomeration economies on productivity growth.

This thesis consists of three empirical chapters. Chapter 5 offers an initial empirical analysis of the effect of agglomeration economies on firm-level productive efficiency. This is done by simultaneously estimating the stochastic production function and the inefficiency function in a one-stage procedure, following Battese and Coelli (1995). The estimation is performed using aggregate manufacturing industry data from 2004 to 2009. In addition to agglomeration economy variables, firm and industry characteristics are included in this estimation. Two important spatial variables, namely urban regions and industrial complexes, are added to the model to support the analysis of the impact of agglomeration economies.

Chapter 6 continues the discussion from Chapter 5 by providing an analysis of the decomposition of total factor productivity growth. Following O'Donnell (2012), the decomposition is computed by using the Färe-Primont productivity index under the assumption that production technology exhibits variable returns to scale (VRS) and that in any given period all sectors must experience the same estimated rate of technical change. Four sources of productivity growth are discussed, namely technical change, efficiency change, technical efficiency change, and scale-mix efficiency change. The decomposition of TFP growth is performed at the three-digit ISIC level, covering more than 50 industry sub-sectors, using data from 2000 to 2009. Industries that achieved maximum productivity are also identified in this analysis.

Chapter 7 is the third empirical chapter. It provides an analysis of the effects of agglomeration economies on productivity growth. Using static and dynamic models, productivity growth as the dependent variable is regressed against agglomeration economy variables and firm characteristics. The analysis is conducted in the aggregated and at the two-digit ISIC level, covering 21 industry sub-sectors from 2000 to 2009. The analysis of the industry sub-sectors is intended to yield broader insights into the effects of agglomeration economies on productivity growth, since industry sub-sectors have different structures, behaviours, and characteristics.

Finally, Chapter 8 concludes the study, discussing key findings and policy implications. Study limitations and suggestions for future research are also presented in this chapter.

Chapter 2
Industrial Development, Policies and Agglomeration in Indonesia

2.1. Introduction

Contemporary industrialization in Indonesia was initiated in 1966 when the "New Order Regime" under President Soeharto gained control over the government after the onset of a series of radical political crises, especially in 1965 (Hill 1990a).[3] However, the effective industrialisation process actually was begun and accelerated in the early 1970s following sound macroeconomic stabilisation and open economic policies, which were commenced by the new order government (Soehoed 1988; Hill 1990a). In 1965, the Indonesian economy was contracting, inflation had reached more than 1,000 percent, and the country was disengaging from the international community. The economic situation was transformed by 1969 when macroeconomic conditions were secure and the inflation rate was brought down to 19 percent (Hill 1996).

Similar to many developing countries, Indonesia has adopted a strategy of rapid industrialisation by promoting the industries that use relatively simple technology and are labour-intensive, such as textiles and garments (Felipe and Estrada 2007); or resources-based, such as food and beverages. In addition, several important industrial policies were implemented in different development stages, such as introducing the import-substitution strategy in the 1970s. This strategy was conducted at the same time as the oil boom era that began in 1973 (Ishida 2003). Since 1967, the Government of Indonesia has implemented six industrialisation stages (Ministry of Industry Republic of Indonesia 2009), with different targets, achievements, policies and challenges. As a result, the structural transformation from an economy dominated by the agriculture sector to manufacturing industry has been successfully made.

[3] From 1945 to 1966, known as the "Old Order Regime", Indonesia faced very unstable political conditions caused by international conflict, specifically with Dutch colonialism in the early days of independence until the 1950s. The failure of parliamentary democracy in this period triggered national pressure from political parties and organized groups in civil society (Rock 1999). The climax situation occurred in 1965 when the Indonesian Communist Party tried to carry out a coup d'état in the Indonesian government. The unstable political and national security conditions contributed to very poor performance of the Indonesian economy under the "Old Order Regime".

The success of the structural transformation at the national level was followed by substantial progress in regional and spatial industrial development. By 2009, Indonesia had 34 provinces and approximately 497 districts and municipalities. The general economic framework shows that economic activities and more specifically the manufacturing industry tends to be concentrated in particular regions, such as around Jakarta (the capital of Indonesia) and other major provincial capitals, for example, Surabaya, Bandung, Semarang, Palembang, Medan and Batam. The concentration of industry around major provincial capitals is a natural process, because those cities serve as the centre of economic growth, which has potential access to markets, economic resources, and bureaucracy. The accessibility of adequate infrastructure attracts the firms to locations around the centre of economic growth. Although the benefits of regional industrial development are still enjoyed by certain regions, but the phenomenon of spatial concentration confirms the existence of the agglomeration process, which is important for stimulating regional growth and productivity.

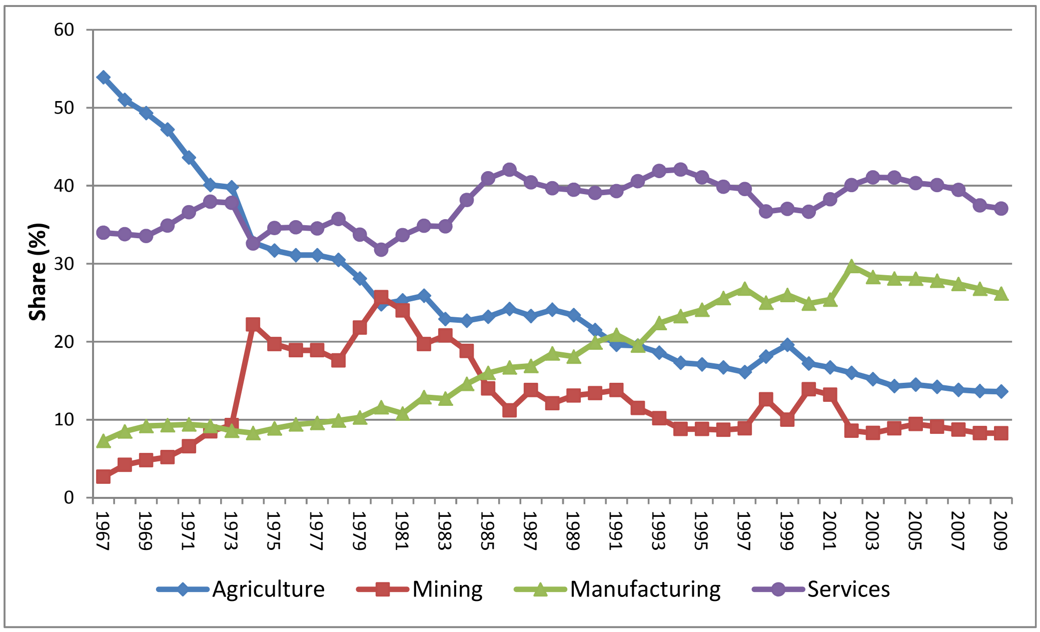
The purpose of this chapter is to analyse Indonesian manufacturing development, policies and performance, more specifically in the context of spatial industrial development and industrial agglomeration. The remainder of the chapter is organised as follows: Section 2.2 briefly discusses the structural transformation from the agriculture to manufacturing industry. The periods of industrial development, policies and strategies are outlined in Section 2.3. Section 2.4 analyses the key performance indicators of the manufacturing industry within the industrialisation stages. Section 2.5 discusses regional industrial development and agglomeration, which continues with the analysis of industrial development within the framework of the national development plan in Section 2.6. Finally, Section 2.7 provides the conclusion.

2.2. Structural Transformation

Structural transformation from the agriculture sector to manufacturing industry is one of the key factors in economic policies, which plays a substantial role in the course of development. Structural transformation is also a success indicator of industrialisation, which is generally viewed as the shift in sectoral contributions to GDP and labour absorption from the agriculture to manufacturing industry. Economists believe that the movement of labour from the agriculture sector to industry is the key factor to enhancing economic activities that promote economic growth (Rodrik 2006).

In a relatively short period, since the mid-1960s to just before the economic crisis in 1997, Indonesia has transformed from a stagnant economy dominated by the agrarian sector to one dominated by a strong manufacturing industry with its exports driving sustained economic growth (Jacob 2005). The structural transformation in Indonesia from 1967 to 2009 is illustrated in Figure 2.1.

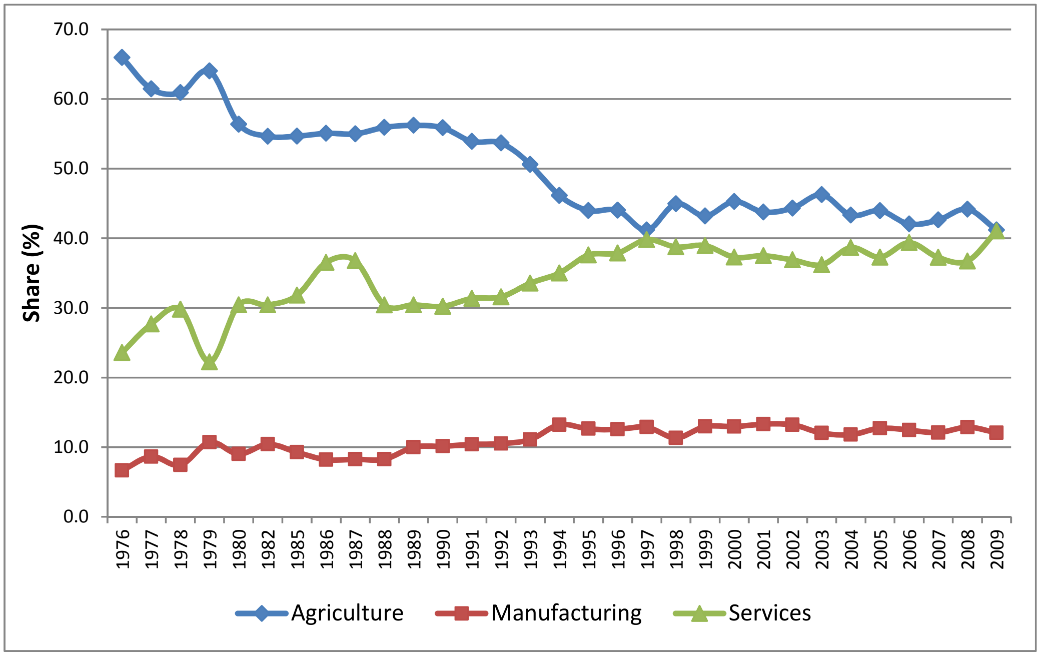
Figure 2.1: The Share of Manufacturing Industry to Gross Domestic Product (GDP), 1967–2009 (%)



Source: Gross Domestic Product by Industrial Origin, Statistics Indonesia *(Badan Pusat Statistik-BPS)*, various publications.
Note: The services sector consists of the government and private services; finance, real estate and business services; transport and communication; and trade, hotel and restaurants.

While transitioning through specific industrialisation stages and the challenges of dynamic macroeconomic development, the manufacturing share of GDP increased substantially from only 7.3 percent in 1967 to 26.2 percent in 2009. Conversely, the agriculture share to GDP declined from 53.9 percent in 1967 to only 13.6 percent in 2009. Meanwhile, the contribution of the services sector to GDP was the highest and it tended to be consistent during this period, in which its share moved around 30 to 40 percent. In addition, the contribution of trade, hotel and restaurants; transportation and communication; finance and banking; and government and private services were 16.9 percent, 8.8 percent, 9.6 percent and 9.4 percent, respectively. Another indicator reflecting the structural transformation was the share of labour to total employment, where the manufacturing contribution increased from 6.7 percent in the 1976 to 12.1 percent in 2009. Figure 2.2 shows the change in the contribution of manufacturing to national employment.

Figure 2.2: The Share of Manufacturing Industry to National Employment, 1976–2009 (%)



Source: Employment Statistics, Statistics Indonesia (http://dds.bps.go.id/eng/tab_sub/view.php?tabel=1&daftar=1&id_subyek=06&notab=2, accessed Aug 21, 2010); Labour Statistics Database, International Labour Organization (ILO), http://laborsta.ilo.org/STP/guest, accessed Aug 20, 2010); World Development Indicators, The World Bank (http://databank.worldbank.org/, accessed Aug 20, 2010). In years 1981, 1983 and 1984, the data was not available.

Note: The services sector consists of the government and private services; finance, real estate and business services; transport and communication; and trade, hotel and restaurants.

In spite of this structural transformation, in fact, the change in the manufacturing contribution to national employment is smaller than the change in its contribution to GDP. This difference indicates that the productivity of the manufacturing industry is higher than that of the agriculture sector, which is in line with the labour movement hypothesis that prevails in a rapid industrialisation process. The success of structural transformation in rapid industrialisation should be accompanied by labour movement from the agriculture sector to the manufacturing industry. However, the path of the labour movement from the agriculture sector to manufacturing industry should be carefully interpreted due to the specific conditions surrounding the agriculture sector.

In Indonesia, the agriculture sector is dominated by un-skilled labour and subsistence-level farmers. Consequently, this labour profile is less suitable with the employment demands in the manufacturing industry, which requires more skilled labour.

In contrast to Indonesia, some Newly Industrialized Economies (NIEs) experienced de-industrialisation during the period of the 1970s to 2004. The reason for this was not because of the deterioration of the manufacturing industry, but due to natural dynamic development processes such as the transition to service-led economies. Felipe and Estrada (2007) state that China and Hong Kong have clearly decreased the level of the manufacturing employment share to GDP by around 25 percent during the same period. This was a significant, but smaller, decline compared to that faced by the countries of South Korea, Singapore and China-Taipei.

Another important trend is the accompanying of rapid industrialisation in Indonesia with structural change within the manufacturing industry. Table 2.1 shows that the value-added share for the food and tobacco industry declined consistently from 14.17% and 24.44% from 1976–1980 to only 11.41% and 10.44% from 1991–1997. Those industries were replaced by new emerging industries, such as basic metals, electrical equipment, and transport equipment. Hill (1990a) states that a major dimension of Indonesia's industrial transformation during the period of the 1970s to 1990s lies in its rapid diversification. In addition, Rodrik (2006) asserts that product diversification is a key correlate to economic development. Moreover, the structural transformation within manufacturing in Indonesia clearly shows the shift from light industries that are labour-intensive to heavy industries that are capital or technology intensive.

Table 2.1 also shows the path of structural transformation within manufacturing industries, which tends to follow the existence of industrial policies in each industrialisation stage. The wood products industry, for example, reached to a significant achievement during 1986–1990 with a share of 11.29%, and then declined to 7.96% during 1991–1997. This occurred due to the government policy change on the exploitation of forest resources. The establishment of "special rights" for forest resource exploration, commonly called *Hak Pengusahaan Hutan – HPH* by certain business groups, has accelerated the wood industry's production since 1990. Unfortunately, this policy conflicted with the "Green Development" program and it was opposed by the international community. Consequently, wood industry production declined after 1990.

Table 2.1: The Share of Value Added in Selected Medium and Large Manufacturing Industries 1976–2009 (% of total)

Industries	1976-1980	1981-1985	1986-1990	1991-1995	1996-2000	2001-2005	2006-2009
Food and Beverages	14.17	11.25	11.45	11.94	11.16	12.73	16.67
Tobacco	24.44	22.08	14.25	10.74	10.02	11.54	8.77
Textile	11.89	9.66	10.17	10.53	10.77	7.07	5.94
Wood Products	4.11	7.09	11.29	8.62	6.26	5.59	2.62
Chemical	11.17	11.40	9.30	9.39	10.03	10.49	14.67
Basic Metal	2.62	6.39	9.25	6.65	5.69	4.51	4.06
Electrical Equipment	3.62	3.95	2.67	4.22	7.42	5.52	5.25
Transport Equipment	4.92	6.63	6.23	9.16	9.77	11.35	13.15

Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Similar to the wood products industry, the share of the basic metals industry also increased consistently from 2.62% in the period 1976–1980 to 9.25% from 1986–1990. This rising contribution is not merely because of technological upgrades but also the role of government policy termed the "Strategic Industries Policy" or *"Kebijakan Industri Strategis",* which has been implemented since the 1970s when B. J. Habibie chaired the Ministry of Research and Technology. This policy is managed by the Agency for Strategic Industry *(Badan Pengelola Industri Strategis – BPIS)* and consists of 10 State Owned Enterprises (SOEs), which provide deep involvement in strategic industries, including the aircraft manufacturer (PT IPTN); steel factory (Krakatau Steel), shipbuilder (PT PAL), telecommunications provider (PT TELKOM), and engineering, defence industry major (PT PINDAD), and other factories (Hill 1996). Nevertheless, the share of the basic metal industries has tended to slow down in the period 1991–1997 in line with the sluggish development in those strategic industries.

2.3. Periods of Industrial Development, Policies and Strategies

Since the mid-1960s, Indonesia has experienced at least six main periods of industrialisation; however there is no definitive agreement between Indonesian scholars regarding this issue. Figure 2.3 illustrates the chronological pattern of industrialisation, which progressed from the period of rehabilitation and stabilisation

(1967–1972) up to the period of recovery and development (2005–2009). Beyond 2009, the period is recognised as rapid industrial growth, which remains part of the long-term industrial development program for 2005–2025. Two of the most important aspects in each stage are the industrial development strategy and market orientation.

Figure 2.3: The Periods of Industrialisation 1967–2009

Industrial Development Policies	Period of Rehabilitation and Stabilization (1967-1972)	Period of Oil-Booming (1973-1981)	Period of Oil Price Declining (1982-1985)	Period of Oil Price Declining (1986-1996)	Period of Economic Crisis and Recovery (1997-2004)	Period of Recovery and Development (2005-2009)
Industry	Import Substitution		+ - Deepening Industrial Structure - High Technology Industrial Based	+ Export Orientation Industries	Revitalization, Consolidation, and Restructuring Industries	+ Development of Prioritized Industries based on Cluster and Regional Approach
Orientation	Inward Looking			Outward Looking	Inward and Outward Looking	

Sources: The Blueprint of National Industrial Development Policies, Ministry of Industry Republic of Indonesia, 2005.

2.3.1. Period of Rehabilitation and Stabilisation (1967–1972)

The period of rehabilitation and stabilisation was a fundamental period in industrial development policy following the severe political crises in the 1960s. The first action taken by the government was to run with stabilisation and rehabilitation as the necessary conditions for industrialisation as a whole. Starting in 1966, the New Order government encouraged an open national economy by establishing policies covering the relaxation of restrictions on imports and exports, liberalisation of investment policy, and adoption of orthodox monetary and fiscal policy (Jacob 2005). In 1967, the government launched a more favourable investment law, Law No. 1/1967, regarding foreign direct investment, and then followed up with Law No. 6/1968, regarding domestic investment. These laws were directed at attracting capital inflow and enhancing the country's capacity to finance development (Aswicahyono and Feridhanusetyawan 2004). Moreover, both laws were recognised as the initial steps in Indonesia's opening up of its economy to an international environment after experiencing a strictly closed economy during the "Old Order" government era.

In accordance with these policies, Hill (1996) states that by adopting a prudent macroeconomic strategy and more liberal microeconomic policies or open-door policies, the Indonesian economy gradually recovered from the crisis and political instability. Hyperinflation decreased sharply from more than 1,000 percent in 1966 to 15 percent by 1969. Open economic policy and prudent macroeconomic strategy has accelerated economic growth and industrial development. As stated by Wie (2006), Indonesia's rapid industrial growth could be achieved during the late 1960s and early 1970s due to the liberalisation of economic policies. However, starting in the 1970s, the government was more selective about foreign investment by restricting some vital economic sectors.

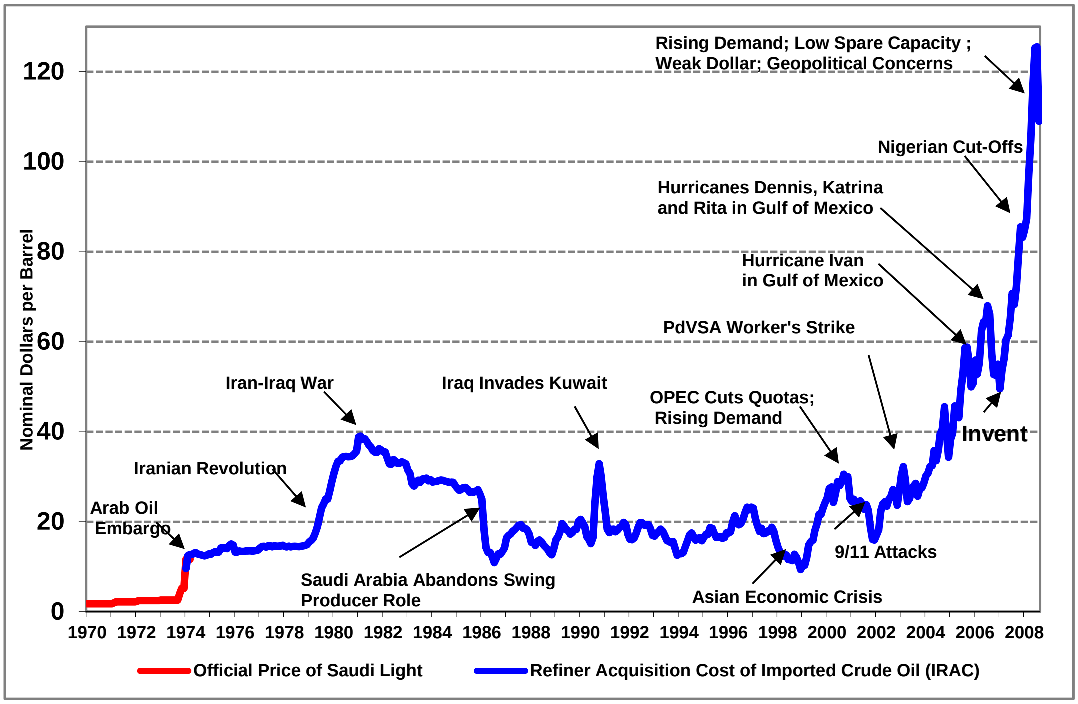
In the period of stabilisation and rehabilitation, the Indonesian government implemented an import substitution strategy and an inward looking orientation in 1969, together with the announcement of the First Five-Year Program *(Repelita I)*. The industries prioritised for industrialisation were fertilizers, cement and agricultural machinery. In the same period, the government also launched a policy for the promotion of domestic production of automobiles. This policy and strategy was then followed-up by other trading policies, such as import tariffs and import barriers especially those targeting the manufacturing sector (Ishida 2003). The import substitution period was characterised by a major role of State Owned Enterprises (SOEs), which either created new businesses or expanded capacity at existing firms.

2.3.2. Period of Oil Boom (1973–1981)

The oil boom started in 1973 and made a substantial contribution to Indonesia's economic and industrial development. As a major oil-producing nation, Indonesia became very rich in a short time. Figure 2.4 indicates the trends of world oil prices from the 1970s to 2008. As a result, from 1973 to 1981, Indonesia obtained an enormous windfall from sky rocketing world oil prices.

In a stronger economic environment, the government was encouraged to change some industry and trade policies, even though it continued to implement the import substitution plan and inward looking strategy. The main industrial policies shifted to focusing on strong government intervention and protection. Restrictions on foreign capital prevailed for almost all foreign-affiliated companies to increase the share of national capital to 51% or more within 10 years. Meanwhile, in the industrialisation process, the government relied greatly on the SOEs (Ishida 2003). Consequently, the state played a more vigorous and dynamic role in financing, protecting and subsidising both domestic capital and direct investment (Dhanani 2000).

Figure 2.4: Trends in World Oil Prices 1970–2008 (Nominal Price, USD per Barrel)



Source: Energy Information Administration (EIA),
(www.eia.doe.gov/emeu/cabs/AOMC/images/chron_2008.xls, accessed May 25, 2010)

The rapid manufacturing growth during the oil boom era was boosted by protectionist import substitution policies. This is the second stage of the import substitution policy that was implemented by the government following the "success" of the first stage of import substitution, which was completed in the mid-1970s. The second stage of the import substitution policy covered the establishment of various upstream industries, SOEs and basic industries (Wie 2006), and also heavy industrial capacity, such as steel, natural gas, oil refining and aluminium, which were all based on natural resources (Dhanani 2000).

2.3.3. Period of Oil Price Declining (1982–1996)

After around eight years enjoying benefits from the windfall of high oil prices, Indonesia entered 1982 with high dependency on oil revenues. The oil and gas industry contributed approximately three-quarters of merchandise exports and two-thirds of government revenue. In contrast, the share of manufacturing exports was only around 2 percent of merchandise exports (Hill 1996). The high dependence on oil revenue resulted in Indonesia's economy being placed in a vulnerable position. As pointed out in Figure 2.4, oil prices began to decline gradually in early 1982, and then down sharply in 1985–1986. The decline in oil prices had a significant impact on manufacturing development and the national economy as a whole, and it was equivalent to around 15 percent of GDP over the period 1986–1988 (Hill 1996). Moreover, this episode was virtually a turning point in the national development strategy, as the state-led industrialisation funded by oil revenues finally failed.

To recover from the crisis, the government established economic policies at both the microeconomic and macroeconomic level. This was done first by correcting the protectionist policy during the oil boom to become a free-market and open economy, and second by seeking more aid and funding from international donor institutions such as the International Bank for Reconstruction and Development (IBRD) and Inter Governmental Groups on Indonesia (IGGI). Thirdly, the government provided more sound and friendly macroeconomic policies, for instance, devaluation of the rupiah by around 28 percent in 1983, which was followed by another devaluation in 1986, tight monetary and fiscal policy, and reform in the financial and banking sector (Hill 1996; Dhanani 2000). Nevertheless, those policies only had a slight impact on the macro economy. Manufacturing exports reached only 11 percent of total exports in 1984 (Dhanani 2000).

Following the policies above, the government also introduced and adopted an export-oriented industrialisation strategy or outward-looking orientation, which started in 1986. However, not all industrial sectors followed the open-economy policy or export-oriented strategy. With his strong power and influence, the minister of research and technology continued the protection of high technology-based industries, specifically for areas called “strategic industries”, which remained fully managed by SOEs. In other words, those sectors were still following the state-led industrialisation strategy.

Another closed-economy industry was the forest sector. The government restricted log-exports and encouraged plywood exports in order to promote and increase higher value forest production. Meanwhile, there was still an extensive decline in foreign investment, which was only gradually reduced. This situation changed in mid-1994 after new regulations on foreign investment were produced by the government, providing foreign investors with much broader access to this sector (Dhanani 2000).

The open-economy policy was followed by a series of macro economy policies, which finally accelerated manufacturing growth from around 13 percent from 1985–

1988 to 20 percent from 1989–1993. Manufacturing exports also grew from $500 million in 1980 to $2.6 billion in 1986, and then consistently increased to $9.04 billion and $19.43 billion in 1990 and 1993, respectively. From 1983 to 1993, manufacturing exports grew almost 30 percent per annum. Nevertheless, after notable achievements, manufacturing growth declined during 1994 to 1997 to only 12 percent per annum (Hill 1996).

2.3.4. Period of Economic Crisis and Recovery (1997–2004)

In this period, the government had a narrower focus on the revitalisation, consolidation and restructuring industries with a mixed market orientation, of both inward and outward-looking policies. An economic crisis in 1998, triggered by a monetary crisis in mid-1997, created the worst period in the industrialisation stages since the severe political and economic chaos in mid-1965. As outlined in Table 2.2, due to the initial impact of the monetary crises in 1997, the manufacturing industry declined to 5.3% growth from 11.6% in the previous year. In 1998, manufacturing industry declined sharply by -13.1% (non-oil and gas) and -11.4% (including oil and gas).. This was the peak of the economic crises, which was accompanied by massive firm bankruptcies and a high unemployment rate. The level of employment in the manufacturing industries decreased from 11.01 million in 1997 to 9.93 million in 1998, or around -9.8 percent. Moreover, almost all manufacturing sectors contracted in 1998 and some of those fluctuated for a few years, for instance, wood products, iron and basic metals.

The economic crisis in 1998 proved that, in spite of remarkable achievements in manufacturing development prior to 1997, serious structural weaknesses existed surrounding this sector. One of these was the high dependency on raw materials and intermediate products imported for certain industries, especially for high capital and technological intensive industries. Nevertheless, Dhanani (2000) argues that, for large and medium scale manufacturing, the economic crisis only led to a moderate impact whereby production and capacity utilisation decreased less than 10 percent, the employment rate declined less than 3 percent, industrial concentration remained unchanged and overall manufactured exports were still at the pre-crisis level.

Table 2.2: Gross Domestic Product (GDP) Growth by Industrial Origin 1996–2004 (%)

Industrial Origin	1996	1997	1998	1999	2000	2001	2002	2003	2004
Agriculture, Livestock, Forestry and Fishery	3.1	1.0	-1.3	2.2	1.9	1.7	2.0	2.5	2.8
Mining and Quarrying	6.3	2.1	-2.8	-1.6	5.5	1.3	2.5	0.5	-4.5
Manufacturing Industry	11.6	5.3	-11.4	3.9	6.0	3.1	3.4	3.5	6.4
Oil and Gas Manufacturing	11.1	-2.0	3.7	6.8	-1.7	-3.5	1.2	0.6	-1.9
Non Oil-Gas Manufacturing	11.7	6.1	-13.1	3.5	7.0	3.9	3.7	3.8	7.5
Food, Beverages and Tobacco	17.2	12.3	-0.2	4.6	3.6	2.3	2.6	2.1	1.4
Textile, Leather Products & Footwear	8.7	-3.8	-14.9	8.5	8.0	4.3	4.5	3.7	4.1
Wood Products and other Wood Prod.	3.2	-2.9	-25.5	-13.5	6.9	-0.3	0.0	1.9	-2.1
Paper and Printing	6.9	8.4	-4.0	2.3	2.6	-5.7	2.9	7.9	7.6
Fertilizers, Chemical and Rubber Prod.	9.0	3.5	-16.0	10.3	7.1	5.0	7.0	10.4	9.0
Cement and Non Metal Min. Prod.	11.0	3.5	-29.8	5.2	5.5	12.3	10.1	6.3	9.5
Iron and Basic Steel	8.0	-0.5	-26.9	-0.2	13.1	-0.3	3.2	-1.6	-2.6
Trans. Equip., Mach. and Apparatus	4.6	-1.1	-52.3	-10.3	43.5	20.3	4.8	4.3	17.7
Other Manufacturing Products	9.7	6.8	-36.0	-1.5	12.8	21.0	10.2	7.9	12.8
Electricity, Gas and Water Supply	13.6	12.4	3.0	8.3	7.6	8.2	6.0	6.8	5.3
Construction	12.8	7.4	-36.4	-1.9	5.6	4.4	4.9	6.7	7.5
Trade, Hotel & Restaurant	8.2	5.8	-18.2	-0.1	5.7	3.7	3.8	3.7	5.7
Transport and Communication	8.7	7.0	-15.1	-0.8	8.6	7.8	8.0	10.7	13.4
Financial, Ownership and Business Services	6.0	5.9	-26.6	-7.2	4.6	5.4	5.7	6.3	7.7
Services	3.4	3.6	-3.8	1.9	2.3	3.1	2.1	3.4	5.4
Gross Domestic Product	**7.8**	**4.7**	**-13.1**	**0.8**	**4.9**	**3.5**	**3.7**	**4.1**	**5.0**
Gross Domestic Product (Non-Oil)	**8.2**	**5.2**	**-14.2**	**1.0**	**5.3**	**4.2**	**4.1**	**4.6**	**5.9**

Source: Gross Domestic Product (GDP) by Industrial Origin, Statistics Indonesia, various publications (http://www.bps.go.id/aboutus.php?tabel=1&id_subyek=11, accessed August 21, 2010)

To overcome the economic crises, the government cooperated with the International Monetary Fund (IMF) on country technical assistance and requested financial support. In addition, the government signed a series of Letters of Intent (LOI) containing broad programs to rehabilitate Indonesia's economy, including a section on deregulation and privatisation, which related to the industrial restructuring. The first specific industrial policy after the economic crisis was officially established by the government in 2001, the well-known "Industrial and Trade Development Policy 2001". Basically, this policy mostly refers to the national document called *"Garis-garis Besar Haluan Negara–GBHN"* or "Blueprint of Medium Term Development Framework" 1999–2004 and Law No. 25/2000 regarding the National Development Program 2000–2004. There is no particular policy initiative specifically directed to bringing the manufacturing industry out of the economic crisis.

In the period 1999 to 2004, the manufacturing industry gradually achieved positive growth with an average rate around 3.4%, except in 2000. Surprisingly, the growth rate achieved was 6%, which was the highest level after the crisis. This was driven by some major industries, which returned to high growth in 2000, such as transport equipment and machinery (43.5%), iron and basic metals (13.1%) and wood products (6.9%). Wie (2006) emphasises that, to some extent, the sluggish growth in manufacturing after 2000 was caused by lower production output from the oil and gas industries, specifically the petroleum refineries.

2.3.5. Period of Recovery and Development (2005–2009)

While maintaining the previous programs, the government broadened the policies covered during 2005-2009 by focusing on the development of prioritised industries based on an industrial cluster and regional approach. Three crucial documents were released in 2004 and 2005: (1), National Medium Term Development Plan 2004–2009 *(Rencana Pembangunan Jangkan Menengah Nasional–RPJMN)*; (2), National Long Term Development Plan 2005–2025 *(Rencana Pembangunan Jangka Panjang Nasional –RPJPN)*, and (3), National Industrial Development Policy 2005.

The first two documents provide the basic frameworks for the whole national development plan over the medium-term and long-term spectrum, and the third document provides specific policy on industrial development. The most recent government policy on industrial development is the President Regulation No. 28/2008 regarding National Industrial Policy. Those documents are inter-related to each other with the main goal being to bring back the manufacturing industries as the engine of economic growth in long-term national development.

The government also addressed serious concerns about Indonesian economic geography. Since 2001, Indonesia has implemented a decentralisation program, or regional autonomy, which has shifted the financial resources and administrative authority from the central to regional government especially the third-level tiers (i.e., districts *(kabupaten)* and municipalities *(kota)*). Then, decentralisation was followed by large regional fragmentation *(pemekaran wilayah)*, which signalled a new challenge in harmonising regional industrial policy. Major reform on economic and industrial policy since the 1970s has resulted in rapid industrialisation, in which most industrial activity is concentrated mainly in Java and Bali. As recognised, these regions' share of value added and employment in manufacturing industries reached approximately 75-80%. More specifically, these manufacturing industries concentrate mainly on certain groups of regions, such as, *Jabodetabek* (Jakarta and surrounding areas) and *Suramadu* (Surabaya and surrounding areas) (Hill et al. 2008; Hill 1990b).

2.4. Stages of Industrial Development and Performance Indicators

This section expands the analysis of the performance and structure of manufacturing industries discussed in the previous section. The analysis focuses on the comparison of key indicators between the periods or stages of industrial development.

2.4.1 Manufacturing Contribution to Economic Growth

In line with the structural transformation, manufacturing contribution to economic growth is also a crucial indicator during the industrial development stages. Table 2.3 below describes the comparison between economic growth and manufacturing growth based on the periods of industrial development from 1967 to 2009. The average manufacturing growth is higher compared to aggregate economic growth in all industrial development stages except for the period 2005–2009, while the most impressive performance is achieved from 1976 to 1996 with average growth reaching 13.4 percent. Hayashi (2005) states that in the period from 1976 to 1981, manufacturing development gained from high oil revenues (oil boom). In the period from 1982 to 1996, although the oil price starts to fall in 1982, the government was able to maintain a high rate of industrial growth due to the implementation of the macroeconomic adjustment program. The comparison of the annual growth rate is described in Figure 2.5.

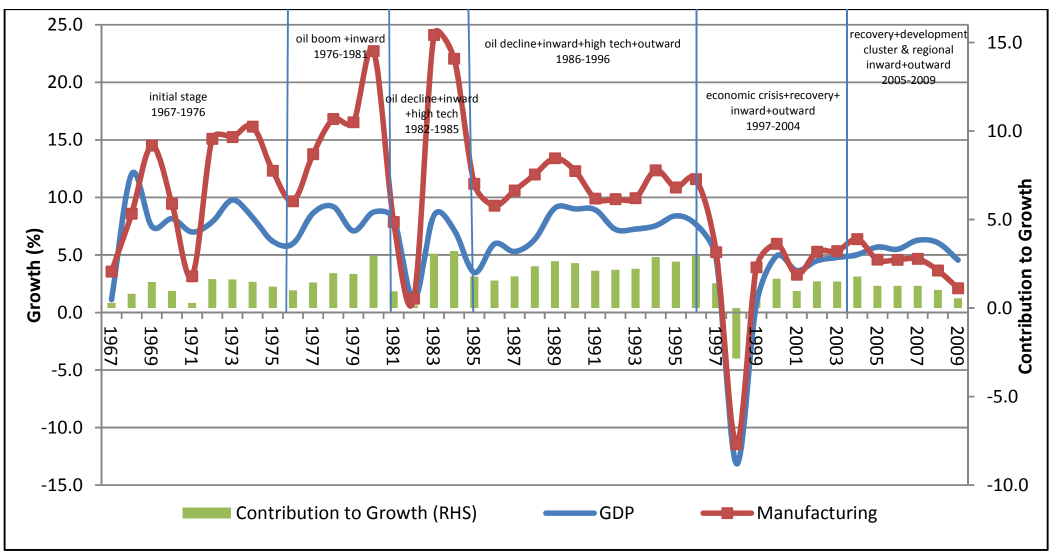
However, in the early years of long-term industrial development (2005–2009), manufacturing growth was lower than economic growth. After facing an economic crisis in 1998, it was difficult to accelerate growth in manufacturing industries due to internal and external problems, such as weak linkages between downstream and upstream industry, a limited high-technology industry, institutional challenges, and so forth (The Ministry of Industry 2009).

Table 2.3: Manufacturing Contribution to Economic Growth by the Stages of Industrial Development, 1967–2009

Indicators	Periods and Strategy					
	Rehabilitation and Stabilization (1967-1972)	Oil Boom (1976-1981)	Oil Price Decline (1982-1985)	Oil Price Decline (1986-1996)	Economic Crisis and Recovery (1997-2004)	Recovery and Development (2005-2009)
	Inward Looking (IL)	Inward Looking (IL)	High Tech & IL	High Tech & Outward Looking (OL)	Revitalization, IL and OL	Cluster, Regional Approach, IL and OL
Economic Growth (average, %)	6.2	8.0	5.1	7.5	1.9	5.6
Manufacturing Growth (average, %)	7.8	14.6	14.6	11.1	2.3	3.9
Contribution to Economic Growth	0.6	1.6	2.0	2.3	0.6	1.1

Source: Gross Domestic Product (GDP) by Industrial Origin, Statistics Indonesia, various publications, author's calculation (http://www.bps.go.id/tab_sub/view.php?tabel=1&daftar=1&id_subyek=11&notab=3, accessed Aug 21, 2010)

Figure 2.5: Manufacturing Contribution to Economic Growth 1967–2009



Source: Gross Domestic Product (GDP) by Industrial Origin, Statistics Indonesia, various publications, author's calculation. (http://www.bps.go.id/tab_sub/view.php?tabel=1&daftar=1&id_subyek=11&notab=3, accessed Aug 21, 2010)

2.4.2. Share of Value Added by Industry

Table 2.4 describes the share of value added by industry sub-sectors to total industry with regard to the stages of industrial development. Several interesting features raised during the industrialisation periods are discussed in the following sub-sections.

Firstly, since industrial development commenced in the early 1970s, two manufacturing industries have consistently sustained their share, namely the food and beverages industry (ISIC 15) and chemical industry (ISIC 24) with an average share of value-added in the period from 1976–2009 of 13.80% and 10.86%, respectively. Two industries that dominated in the early stage of industrialisation, but whose contribution has steadily declined are the tobacco industry (ISIC 16) and textile industry (ISIC 17). The tobacco industry was the largest manufacturing industry in the early stages of industrialisation and contributed 24.32% in the period 1976 to 1981. The domination of labour-intensive industries in the 1970s, such as tobacco and textiles, was in line with the major strategy adopted by the government, in which the manufacturing industry mostly relied on the resources-based sectors.

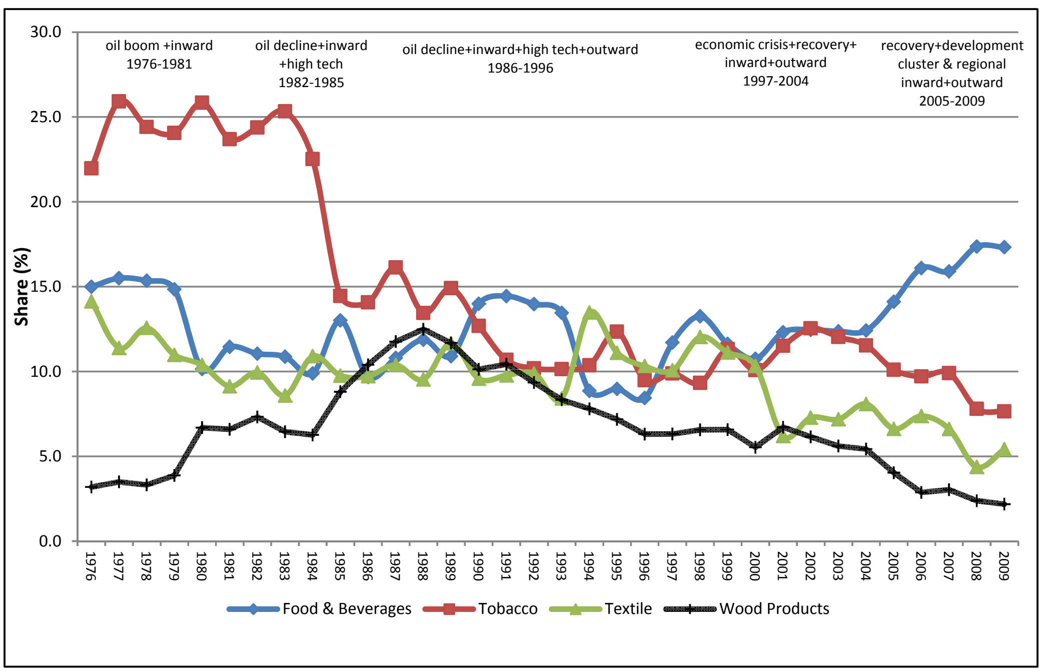
Table 2.4: Industrialisation Stages and Average Share of Value-Added in Manufacturing Industries 1976–2009, (% of total, excluding oil and gas)

KBLI[a]	Industries	Periods and Strategy					Average Share 1976-2009
		Oil Boom (1976-1981)	Oil Price Decline (1982-1985)	Oil Price Decline (1986-1996)	Economic Crisis and Recovery (1997-2004)	Recovery and Development (2005-2009)	
		Inward Looking (IL)	High Tech & IL	High Tech & Outward Looking (OL)	Revitalisation, IL and OL	Cluster, Regional Approach, IL and OL	
15	Food and Beverages	15.93	13.18	12.39	12.90	16.31	13.80
16	Tobacco	24.32	21.67	12.22	10.90	9.04	14.69
17	Textile	11.43	9.79	11.26	8.88	6.08	9.79
18	Garments	0.72	1.45	3.26	3.80	3.43	2.75
19	Leather products	0.94	0.78	2.20	2.76	1.80	1.88
20	Wood products	4.53	7.21	9.62	6.04	2.90	6.61
21	Paper products	1.20	1.12	2.97	5.48	5.75	3.44
22	Printing, publishing and re-production	1.11	1.20	1.44	1.41	1.14	1.30
24	Chemical and chemical products	11.33	11.20	9.32	10.55	13.93	10.86
25	Rubber products and plastics	4.70	4.88	4.76	4.33	5.71	4.80
26	Non-metallic minerals	6.53	5.12	3.67	3.91	4.01	4.45
27	Basic metal	2.83	7.02	8.19	4.26	3.95	5.56
28	Metal products and equipment	2.59	3.24	3.93	2.53	2.71	3.10
29	Machinery	1.44	1.43	1.21	1.91	1.82	1.53
30/33	Professionals equipment	0.07	0.04	0.13	0.32	0.34	0.18
31/32	Electrical equipment	3.66	3.97	3.79	7.10	5.46	4.81
34/35	Motor vehicles and transport equipment	5.63	6.00	7.91	10.37	13.40	8.67
36/37	Furniture and others	0.41	0.43	1.41	2.47	2.22	1.49

Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.
Note: [a] Based on the ISIC 1990 and Indonesian Standard Industrial Classification *(Klasifikasi Baku Lapangan Usaha Indonesia - KBLI)* 1997

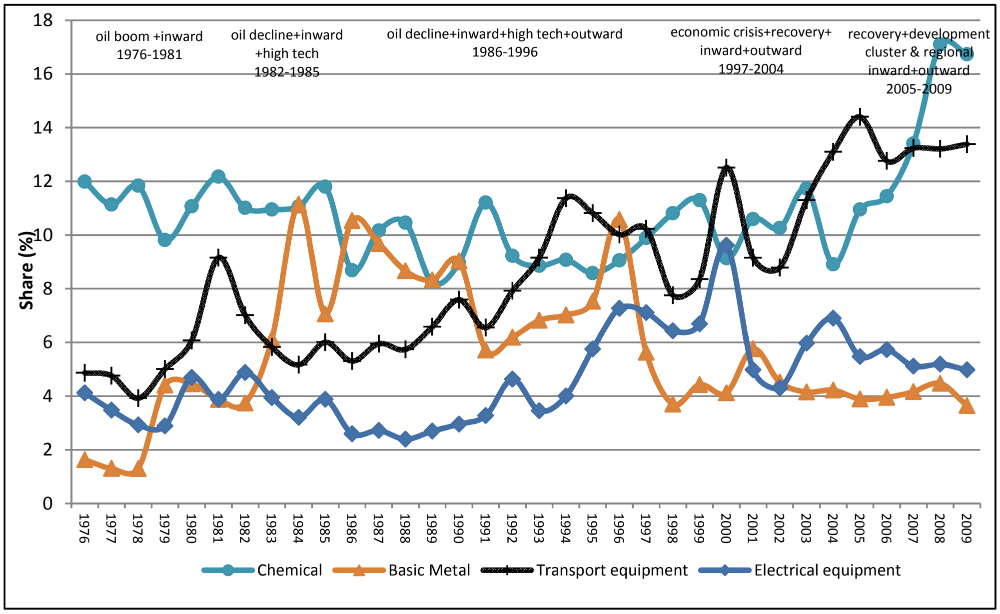
Secondly, the motor vehicles and transport equipment industries (ISIC 34 and 35) showed the most potential. Their shares increased from only 5.63% from 1976–1981 to 13.40% from 2005–2009. Considering current and future growth prospects, the motor vehicles and transport equipment industries were set to be one of the leading industries in the long-run with support from the industrial development policy. Similarly for the paper products industry (ISIC 21), the contribution increased from 1.2 percent in 1976–1981 to 5.79 percent in 2005–2009. The third observation is that the contributions of some industries tended to increase but eventually reached a certain level and then decreased, for example, the basic metals industry (ISIC 27) and wood products industry (ISIC 20). Both industries reached the highest performance in the period 1986–1996 and contributed 8.19% and 9.62%, respectively. Unfortunately, their contributions in the period of 2005–2009 decreased to only 3.95% and 2.90%. Regardless of the arising challenges during the industrialisation stages, Hayashi (2005) points out that the manufacturing industry with high annual growth serves as the main driving force of economic growth and employment absorption.

Figure 2.6: Share of Value Added in Selected Labour-Intensive Manufacturing Industries 1976–2009 (% of total)



Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Figure 2.7: Share of Value Added in Selected Capital-Intensive Manufacturing Industries 1976–2009 (% of total)



Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

In line with Table 2.4, Figure 2.6 and Figure 2.7 describe the fluctuation of the industrialisation path of several main industries from 1976 to 2009, which reflect the role of industrial policies within the structural transformation process. In detail, Figure 2.6 shows the development of selected labour-intensive industries, which are recognised as the leading sectors in the early stages of industrialisation. The tobacco industry (ISIC 16) provided a significant contribution in the mid-1970s to 1982; however, its contribution declined sharply in 1984 following the oil price downturn and the introduction of high technology as the new strategy of industrial development.

Figure 2.7 illustrates the development of selected capital-intensive industries. The contribution of the transport equipment industry is the most interesting feature. Although facing macroeconomic fluctuations and uncertainty, its contribution increased consistently over the last five years and is one of the industries with the most growth potential. Since 2000, automotive production increased from 301 thousand units to 604 thousand units in 2008 for all types, but then slightly decreased in 2009 to 483 thousand units due to the global economic crisis in 2008. However, growth in the automotive market is forecasted to return and its production is targeted to reach 1,250 thousand units in 2015 (Gaikindo 2010). Similarly, the contribution of motorcycle production and its supported industries also tended to increase during the same period.

2.4.3. Share of Employment by Industry

Table 2.5 describes the employment share in the manufacturing industries from the period 1976–2009. Some specific characteristics of labour absorption can be explained in the following discussion. Firstly, employment share in the manufacturing industries has been dominated by labour-intensive industries, including the food and beverages industry (ISIC 15); tobacco industry (ISIC 16); textile industry (ISIC 17); wood products industry (ISIC 21); rubber products industry (ISIC 25); and garments industry (ISIC 18). In the early stages of industrialisation, the textile industry was the largest sector with a share of employment of 22.03% followed by the food and beverages industry, and tobacco industry, with their contribution to employment of 17.70% and 17.12%, respectively. However, in the period 2005–2009, the food and beverage industry was the largest sector (16.10%) followed by the textiles (11.99%) and garments industry (11.33%). For the average contribution from 1976 to 2009, the textiles industry is still in first place (16.48%) followed by the food and beverages industry with a share of 15.88%. The tobacco industry experienced a sharp downturn from 17.12% in the period 1976–1981 to only 7.16% in the period 2005–2009. The garments industry has shown the most growth potential; its share of employment increased consistently from 3.74% to 11.23% in the same period.

The second issue is that other non-labour-intensive industries contributed a relatively high share to employment, including the chemical industry (ISIC 24) and motor-vehicles and transport equipment industries (ISIC 34/35) with a share of 4.66% and 3.58%, respectively, in the period 2005–2009. The industries with a high share of value added but having a low share of labour are indicated to have high labour productivity, such as the chemical industry. Meanwhile, the electrical equipment industry has been a growth sector since its labour absorption increased consistently. The share of employment increased from 2.93% in the period 1976–1981 to 4.82% in the period 2005–2009. This growth was supported by rapid development in the electronic components assembling industry, which mostly depends on the labour in the production process.

Table 2.5: Industrialisation Stages and Average Share of Employment in Manufacturing Industry 1976–2009, (% of total, excluding oil and gas)

KBLI[a)]	Industries	Periods and Strategy					Average Share 1976-2009
		Oil Boom (1976-1981)	Oil Price Decline (1982-1985)	Oil Price Decline (1986-1996)	Economic Crisis & Recovery (1997-2004)	Recovery and Development (2005-2009)	
		Inward Looking (IL)	High Tech & IL	High Tech & Outward Looking (OL)	Revitalisation, IL and OL	Cluster, Regional Approach, IL & OL	
15	Food and Beverages	17.70	16.01	15.80	14.41	16.10	15.88
16	Tobacco	17.12	14.13	7.86	5.86	7.16	9.66
17	Textile	22.03	18.59	16.50	14.03	11.99	16.48
18	Garments	3.74	4.39	7.74	10.46	11.23	7.79
19	Leather products	1.11	0.92	4.30	6.37	4.90	3.91
20	Wood products	5.32	10.19	11.24	9.08	6.03	8.80
21	Paper products	1.25	1.34	1.84	2.62	2.80	2.00
22	Printing, publishing and re-production	2.00	1.94	1.65	1.28	1.31	1.61
24	Chemical and chemical products	6.04	6.55	4.99	4.69	4.66	5.24
25	Rubber products and plastics	5.20	6.69	7.97	7.29	7.72	7.14
26	Non-metallic minerals	4.57	4.60	3.85	3.86	3.95	4.08
27	Basic metal	1.20	1.46	1.12	1.33	1.39	1.26
28	Metal products and equipment	3.73	3.45	3.37	2.80	2.86	3.24
29	Machinery	1.30	1.24	1.01	1.68	1.90	1.38
30/33	Professionals equipment	0.12	0.12	0.21	0.42	0.54	0.28
31/32	Electrical equipment	2.93	2.93	2.82	4.45	4.82	3.53
34/35	Motor vehicles and transport equipment	3.05	3.82	3.26	2.82	3.58	3.23
36/37	Furniture and others	1.14	1.20	3.90	6.41	6.75	4.15

Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.
Note: [a)] based on the ISIC 1990 and *Klasifikasi Baku Lapangan Usaha Indonesia (KBLI)* 1997.

2.5. Regional Industrial Development and Agglomeration

The development of regional industries is one of the most prominent subjects related to national industrial development. Indonesia, which consists of 33 provinces and approximately 497 districts or municipalities in 2009, faces complex challenges in realising equitable regional industrial development. Its achievements in modern industrial development, which started in the early 1970s, shows that manufacturing activities tend to be agglomerated in certain regions, specifically large provincial capitals such as Jakarta, Surabaya, Semarang and Bandung. Through external economies, agglomeration is considered to contribute to regional economic growth and firm productivity. How firms tend to be agglomerated or concentrated is an interesting topic. From the structuralist point of view, this phenomenon could be due to an imbalance in regional development and distribution, so that particular regions obtain more benefit than others. Moreover, from an externalities perspective, this phenomenon emerges due to the benefit received by the economic agents for physical and regional proximity. For further discussion, this section provides an analysis of spatial and regional industrial development that leads to industrial agglomeration.

2.5.1. Regional Distribution of Manufacturing Industry

Geographically, Indonesia is an archipelagic country with around 13,000 islands. It is one of the most spatially diverse nations in terms of its natural resources, population, and the location of its economic activities (Hill et al. 2008). In 2009, Indonesia consisted of 33 provinces and approximately 497 districts *(kabupaten)* and cities *(kota)*. Given this context, Table 2.6 describes the regional concentration of industries based on provincial-level data from 1976–2009; provinces are classified into five major groups of islands, as in Hill (1990a).

As can be seen, manufacturing production and activities are mostly concentrated in Java, which had a share of value added of 86.2 percent in the early stages of industrial development, a figure that decreases to 76.62 percent by 2009. West Java, DKI Jakarta, East Java, and Banten dominates the distribution of manufacturing value- added in Java, while the contribution of Central Java tends to decrease consistently. Yogyakarta has not traditionally a base for manufacturing production. Banten is a new province that emerged in 2005, having fragmented from West Java.

Sumatera has been the second largest island for manufacturing production activity, with the major contributors being North Sumatera, Riau, South Sumatera, and Riau Islands. Following the trend of regional fragmentation, the Riau Islands and Bangka Belitung are new provinces separated from Riau and South Sumatera, respectively. In Kalimantan, the manufacturing industries tend to agglomerate in West Kalimantan and East Kalimantan, which are the two most developed provinces in this island. In Sulawesi, the concentration of industry is in South Sulawesi and North Sulawesi. Two new provinces also emerged in this island: West Sulawesi and Gorontalo, which split from South Sulawesi and North Sulawesi. In other regions of Eastern Indonesia, Bali and Papua have become the main bases for manufacturing production. The new provinces that emerge in this group of regions are North Maluku and West Papua.

Table 2.6: Geographical Concentration of Manufacturing Industry by Provinces 1976–2009 (% of total value added)

	1976	1985	1995	2005	2007	2009
Aceh	0.07	1.63	0.83	0.30	0.37	0.38
North Sumatera	3.78	5.14	4.41	3.35	4.42	3.52
West Sumatera	0.66	0.53	0.62	0.70	0.89	0.87
Riau	0.23	1.81	3.40	4.64	3.91	4.24
Jambi	0.12	0.66	0.59	1.38	1.12	0.55
South Sumatera	5.59	2.20	1.64	1.99	2.70	3.32
Bengkulu	0.00	0.11	0.03	0.04	0.06	0.11
Lampung	0.18	1.39	0.76	1.46	1.38	1.16
Bangka Belitung	-	-	-	0.19	0.73	0.56
Riau Islands	-	-	-	2.92	2.82	2.97
Sumatera	**10.65**	**13.47**	**12.28**	**16.96**	**18.40**	**17.69**
Jakarta	25.72	17.88	17.91	18.07	16.52	13.93
West Java	19.89	25.34	33.78	22.89	22.20	29.41
Central Java	14.53	10.29	6.47	5.49	6.68	5.93
Yogyakarta	1.36	0.39	0.43	0.46	0.28	0.25
East Java	24.73	22.42	23.52	20.28	20.08	17.18
Banten	-	-	-	9.62	10.15	9.93
Java	**86.24**	**76.32**	**82.12**	**76.81**	**75.91**	**76.62**
West Kalimantan	0.85	1.56	1.15	0.83	1.19	0.97
Central Kalimantan	0.35	0.68	0.38	0.24	0.41	0.69
South Kalimantan	0.34	1.66	0.99	0.77	0.60	0.89
East Kalimantan	0.23	2.78	1.47	2.35	1.30	1.18
Kalimantan	**1.76**	**6.68**	**4.00**	**4.20**	**3.51**	**3.74**
North Sulawesi	0.09	1.60	0.14	0.33	0.28	0.23
Central Sulawesi	0.02	0.09	0.04	0.05	0.07	0.04
South Sulawesi	0.80	0.72	0.51	0.86	0.95	0.77
Southeast Sulawesi	0.02	0.04	0.03	0.12	0.14	0.06
Gorontalo	-	-	-	0.02	0.07	0.08
West Sulawesi	-	-	-	0.01	0.06	0.07
Sulawesi	**0.94**	**2.45**	**0.72**	**1.39**	**1.57**	**1.25**
Bali	0.20	0.26	0.23	0.15	0.20	0.32
West Nusa Tenggara	0.07	0.07	0.03	0.02	0.02	0.07
East Nusa Tenggara	0.02	0.04	0.02	0.02	0.03	0.01
Maluku	0.10	0.35	0.27	0.16	0.14	0.14
North Maluku	-	-	-	0.16	0.00	0.00
West Papua	0.02	0.36	0.32	0.02	0.08	0.05
Papua	-	-	-	0.10	0.14	0.10
Eastern Indonesia	**0.41**	**1.08**	**0.89**	**0.64**	**0.61**	**0.70**

Note: Table format is adopted from Hill (1990b)
Source: Large and Medium Industrial Statistics 1976–2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

The islands of Java and Sumatera have long been recognized as parts of Western Indonesia and are more developed than most regions in Eastern Indonesia. Java is the centre of industrial production because of the historical fact that development in Indonesia started on this island. Thus, Java provides numerous advantages for economic agents, specifically the availability of adequate infrastructure and production factors. Notwithstanding this concentration, particular industries are spreading throughout Indonesia, specifically industries that rely on certain production inputs, such as natural resources.

2.5.2. Industrial Agglomeration in Groups of Regions

Table 2.7 describes the industrial agglomeration at more localised administrative levels and in terms of the more specific spatial boundaries within which most firms agglomerate. Jakarta and surrounding areas is still the largest pole of manufacturing production activities, with its value-added share to total national industry reaching 48.0 percent in 2009. In this group of regions, Karawang has emerged as a promising new district that functions as a base for manufacturing production especially after the economic crisis in 1998. The limited capacities of Jakarta, Bogor, Tangerang and Bekasi have enabled Karawang, as the closest district, to become a new base of production.

Meanwhile, the second largest pole of agglomerated industries, Surabaya and surrounding areas, is still dominated by Surabaya, Gresik, and Sidoardjo, where manufacturing industries traditionally have been established. The contribution of this group of regions to national manufacturing value added is 12.4 percent. As with Karawang in Jakarta and surrounding areas, Pasuruan has the potential to become a base of manufacturing industry production in Surabaya and surrounding areas. Turning to another prefecture, Kediri is an area of interest. Its contribution to manufacturing is actually larger than that of Surabaya. As the location of the largest cigarette industry in Indonesia, Kediri contributed around 3.4 percent to total manufacturing value added in 2009. Other important poles of manufacturing industries in Java are Bandung and surrounding areas (3.7%), Semarang and surrounding areas (3.2%), and Surakarta and surrounding areas (1.2%). Outside of Java, there are several regions in which manufacturing industries tend to concentrate, for example Riau (3.0%), the east coast of Sumatera (2.5%), Palembang and surrounding areas (2.8%), Batam and surrounding areas (3.0%) and other regions with a share of value added less than 1 percent, such as Samarinda-Bontang (East Kalimantan), Padang (West Sumatera), and Pangkal Pinang.

Table 2.7: Spatial Distribution of Manufacturing Industry 2009

No	Group of Regions	Value Added (trillion IDR)	Labour (000)	Firm	Share to National Level (%)		
					VA	Labour	Firm
1	**Jakarta and surroundings (J)**	**384.5**	**1358.1**	**5324**	**48.0**	**31.3**	**21.8**
	Jakarta	*110.9*	*311.9*	*1635*	*13.9*	*7.2*	*6.7*
	Serang	*16.3*	*63.8*	*144*	*2.0*	*1.5*	*0.6*
	Tanggerang (regency and city)	*48.5*	*385.8*	*1433*	*6.1*	*8.9*	*5.9*
	Bogor (regency and city)	*91.9*	*179.4*	*765*	*11.5*	*4.1*	*3.1*
	Bekasi (regency and city)	*66.5*	*262.2*	*891*	*8.3*	*6.0*	*3.6*
	Karawang	*31.5*	*106.6*	*288*	*3.9*	*2.5*	*1.2*
	Depok (city)	*4.4*	*27.6*	*96*	*0.6*	*0.6*	*0.4*
	Cilegon	*14.5*	*20.8*	*72*	*1.8*	*0.5*	*0.3*
2	**Surabaya and surroundings (J)**	**98.9**	**654.7**	**3858**	**12.4**	**15.1**	**15.8**
	Surabaya (city)	*22.1*	*140.4*	*845*	*2.8*	*3.2*	*3.5*
	Gresik	*13.6*	*97.2*	*494*	*1.7*	*2.2*	*2.0*
	Sidoardjo	*25.1*	*161.2*	*853*	*3.1*	*3.7*	*3.5*
	Malang (regency and city)	*10.7*	*85.5*	*455*	*1.3*	*2.0*	*1.9*
	Pasuruan	*14.4*	*101.4*	*698*	*1.8*	*2.3*	*2.9*
	Probolinggo (regency and city)	*1.7*	*18.8*	*104*	*0.2*	*0.4*	*0.4*
	Mojokerto (regency and city)	*6.5*	*42.0*	*273*	*0.8*	*1.0*	*1.1*
	Tuban	*4.9*	*8.2*	*136*	*0.6*	*0.2*	*0.6*
3	**Kediri (regency and city) (J)**	**27.2**	**54.8**	**152**	**3.4**	**1.3**	**0.6**
4	**Bandung and surroundings (J)**	**29.8**	**372.4**	**1977**	**3.7**	**8.6**	**8.1**
	Bandung (regency and city)	*13.4*	*234.5*	*1599*	*1.7*	*5.4*	*6.5*
	Purwakarta	*6.8*	*46.2*	*159*	*0.9*	*1.1*	*0.6*
	Cimahi	*7.0*	*70.8*	*136*	*0.9*	*1.6*	*0.6*
	Sumedang	*2.6*	*20.8*	*83*	*0.3*	*0.5*	*0.3*
5	**Riau (OJ)**	**23.7**	**23.3**	**40**	**3.0**	**0.5**	**0.2**
	Pelelawan	*9.9*	*6.5*	*17*	*1.2*	*0.2*	*0.1*
	Dumai	*6.1*	*1.6*	*7*	*0.8*	*0.0*	*0.0*
	Siak	*5.1*	*12.2*	*16*	*0.6*	*0.3*	*0.1*
	Indragiri Hilir	*2.6*	*2.9*	*15*	*0.3*	*0.1*	*0.1*
6	**East Coast Sumatra (OJ)**	**20.3**	**103.5**	**747**	**2.5**	**2.4**	**3.1**
	Asahan	*0.9*	*6.4*	*123*	*0.1*	*0.1*	*0.5*
	Medan	*10.0*	*36.1*	*166*	*1.2*	*0.8*	*0.7*
	Labuhan Batu	*0.6*	*3.7*	*20*	*0.1*	*0.1*	*0.1*
	Deli Serdang	*3.5*	*47.7*	*350*	*0.4*	*1.1*	*1.4*
	Tapanuli Selatan	*0.1*	*0.3*	*2*	*0.0*	*0.0*	*0.0*
	Batu Bara	*3.5*	*5.0*	*48*	*0.4*	*0.1*	*0.2*
	Pematang Siantar	*1.7*	*4.3*	*38*	*0.2*	*0.1*	*0.2*
7	**Palembang and surroundings (OJ)**	**22.3**	**30.6**	**148**	**2.8**	**0.7**	**0.6**
	Palembang (city)	*8.0*	*16.2*	*96*	*1.0*	*0.4*	*0.4*
	Banyu Asin	*3.9*	*11.5*	*37*	*0.5*	*0.3*	*0.2*

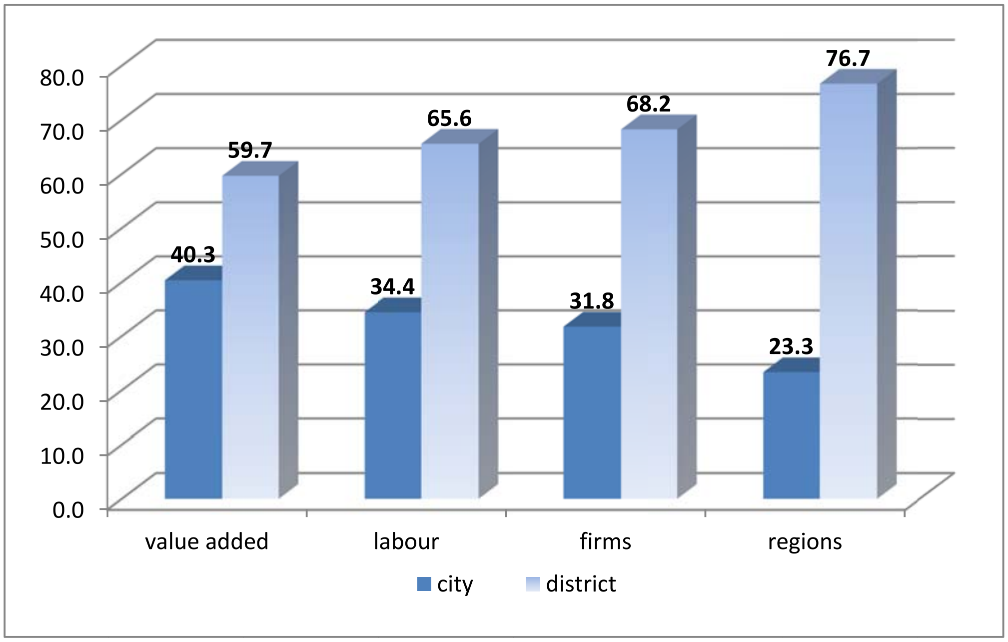
No	Group of Regions	Value Added (trillion IDR)	Labour (000)	Firm	Share to National Level (%)		
					VA	Labour	Firm
	Ogan Ilir	*10.5*	*2.9*	*24*	*1.31*	*0.07*	*0.10*
8	**Semarang and surroundings (J)**	**25.8**	**341.1**	**1484**	**3.2**	**7.9**	**6.1**
	Semarang (regency and city)	*9.8*	*152.9*	*472*	*1.2*	*3.5*	*1.9*
	Kendal	*2.4*	*17.8*	*46*	*0.3*	*0.4*	*0.2*
	Salatiga (city)	*0.6*	*7.6*	*23*	*0.1*	*0.2*	*0.1*
	Kudus	*10.3*	*96.6*	*179*	*1.3*	*2.2*	*0.7*
	Demak	*1.2*	*12.9*	*59*	*0.2*	*0.3*	*0.2*
	Pekalongan (regency and city)	*0.9*	*39.0*	*595*	*0.1*	*0.9*	*2.4*
	Magelang (regency and city)	*0.6*	*14.4*	*110*	*0.1*	*0.3*	*0.4*
9	**Batam and surroundings (OJ)**	**23.7**	**141.9**	**326**	**3.0**	**3.3**	**1.3**
	Batam	*21.8*	*130.0*	*287*	*2.7*	*3.0*	*1.2*
	Bintan	*1.9*	*11.9*	*39*	*0.2*	*0.3*	*0.2*
10	**Surakarta and surroundings (J)**	**9.2**	**141.3**	**895**	**1.2**	**3.3**	**3.7**
	Surakarta (city)	*0.6*	*14.8*	*184*	*0.1*	*0.3*	*0.8*
	Sukoharjo	*4.1*	*47.1*	*145*	*0.5*	*1.1*	*0.6*
	Karanganyar	*2.5*	*45.1*	*155*	*0.3*	*1.0*	*0.6*
	Sragen	*1.5*	*14.5*	*57*	*0.2*	*0.3*	*0.2*
	Klaten	*0.5*	*19.9*	*354*	*0.1*	*0.5*	*1.4*
11	**Samarinda and surroundings (OJ)**	**6.6**	**19.6**	**76**	**0.8**	**0.5**	**0.3**
	Samarinda	*0.4*	*3.9*	*30*	*0.1*	*0.1*	*0.1*
	Balikpapan	*1.7*	*8.3*	*28*	*0.2*	*0.2*	*0.1*
	Bontang	*3.3*	*3.5*	*8*	*0.4*	*0.1*	*0.0*
	Kutai	*1.2*	*3.9*	*10*	*0.2*	*0.1*	*0.0*
12	**Padang (OJ)**	**5.7**	**6.9**	**54**	**0.7**	**0.2**	**0.2**
13	**Pangkal Pinang (OJ)**	**3.0**	**5.2**	**21**	**0.4**	**0.1**	**0.1**
	Total of groups	**680.8**	**3,253.3**	**15,102**	**85.06**	**74.87**	**61.72**

Note: Table format is adopted from Hill (1990b); J=Java, OJ=Outside Java
Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Table 2.7 indicates that the tendency of firms to agglomerate is influenced by the size and the rate of growth of the cities or regions in which they are located. The growing cities or regions attract economic agents, who enter to develop their businesses around the centres of growth. Jakarta and Surabaya and their surrounding regions appear to have the requisite features for agglomeration. Over and above this, industrial agglomeration appears also to be driven by the capacity of a region to provide production inputs, whether raw materials or human resources. Kediri, with its large resource of labour, is a suitable base for labour-intensive industries such as cigarette products. A similar condition exists, for example, for the clay products industry, which tends to agglomerate in the south of Central Java, where high quality raw materials and abundant labour are available.

Figure 2.8 explains the comparison of manufacturing distribution based on the region's status, regency/district *(kabupaten)* and municipality/city *(kotamadya)* in 2009.[4]. From total third-level tier regions, 76.7 percent and 23.3 percent are regencies and cities, respectively. The cities' contributions to value added, labour and number of firms are 40.3%, 34.4% and 31.8%, while regencies are 59.7%, 65.6% and 68.2% respectively.

Figure 2.8: Manufacturing Distribution in City and District 2009 (%)



Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Figure 2.8 clearly describes that urban regions (cities) contribute significantly to value added even though the number of regions is much less than that of the districts. This is a common feature of the industrialisation process in rural (less developed) and urban regions. Better access to services and adequate infrastructure allow the urban regions to grow faster than rural areas. Urban regions tend to be dominated by modern manufacturing industries, such as those of high-technology and capital-

[4] Regency *(kabupaten)* is less developed than municipality/city *(kotamadya)*.

intensive industries. Conversely, non-urban regions are dominated by light and labour-intensive industries.

2.5.3. The Dispersion of Manufacturing Industries

Table 2.8 describes the regional dispersion of the manufacturing industry based on province and district level in 2-digit ISIC for the year 2009. The district is the third-level tier of administrative authority in Indonesia, and is equivalent to counties in countries such as China and the US. Having activity in 68.2 percent of the total regions, the food and beverages industry (ISIC 15) is the only sector that has spread to more than half of total districts. Only the industry of wood products (ISIC 20) has almost the same coverage, at 42.9 percent.

Other industries that are also fairly dispersed at the municipality levels are the furniture and manufacturing n.e.c industry (ISIC 36), other non-metallic mineral industry (ISIC 26), rubbers and plastics industry (ISIC 25), and chemicals industry (ISIC 24). They have coverage of 38.6 percent, 36.8 percent, 33.2 percent, and 28.8 percent, respectively. The rest of industries tended to be concentrated in a small number of districts only. However, some specific industries are concentrated in very limited regions because they depend on the resources used in their production process, such as tobacco industry (ISIC 16), or coal and refined petroleum products industry (ISIC 23). In general, light industry and labour-intensive industry are more widely dispersed than heavy engineering industry or capital-intensive industry, because the establishment of those industries requires less investment and simpler technology.

Table 2.8: The Dispersion of Manufacturing Industries in 2-digit ISIC 2009

ISIC	Industries	Labour (person)	Established in:		District Coverage (%)
			Province	District	
15	Food products and beverages	714,824	32	339	68.2
16	Tobacco	331,548	11	81	16.3
17	Textiles	498,047	24	136	27.4
18	Apparel	464,777	20	113	22.7
19	Tanning and dressing of leather	221,744	13	73	14.7
20	Wood and products of wood, except furniture and plating materials	212,318	30	213	42.9
21	Paper and paper products	120,001	17	76	15.3
22	Publishing, printing and reproduction of recorded media	60,980	31	93	18.7
23	Coal, refined petroleum products and nuclear fuel	6,711	20	42	8.5
24	Chemicals and chemical products	211,667	23	143	28.8
25	Rubber and plastics' products	339,297	24	165	33.2
26	Other non-metallic mineral products	175,127	30	183	36.8
27	Basic metals	60,632	15	45	9.1
28	Fabricated metal products, except machinery and equipment	126,921	20	104	20.9
29	Machinery and equipment n.e.c (not elsewhere classified)	71,276	11	60	12.1
30	Office, accounting, and computing machinery	2,892	5	7	1.4
31	Electrical machinery and apparatus n.e.c	80,529	9	36	7.2
32	Radio, television and communication equipment and apparatus	130,173	7	33	6.6
33	Medical, precision and optical instruments, watches and clocks	19,938	9	30	6.0
34	Motor vehicles, trailers and semi-trailers	85,362	13	53	10.7
35	Other transport equipment	81,761	25	68	13.7
36	Furniture and manufacturing n.e.c	322,741	31	192	38.6
37	Recycling	5,908	11	49	9.9

Note: Number of provinces and districts (city and regency) in 2009 were 33 and 497, respectively.
Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

2.5.4. Regional Fragmentation and the Emergence of New Potential Regions

The change in geographical structure is an important aspect that has affected the spatial concentration of the manufacturing industry, specifically after the decentralisation policy implemented by the government of Indonesia in 2001. The most fundamental change is the fragmentation of regions either in second-level tier regions (province) or in third-level tier regions (regency/city). Table 2.9 describes the regional fragmentation progress from 1999 to 2009.

Table 2.9: Number of New Regions by Province 1999–2009

	Province	New Region				Remarks
		Province	Regency	Municipality	Total	
11	Aceh	0	10	3	13	
12	North Sumatera	0	12	2	14	
13	West Sumatera	0	4	1	5	
14	Riau	0	6	1	7	
15	Jambi	0	4	1	5	
16	South Sumatera	0	5	3	8	
17	Bengkulu	0	6	0	6	
18	Lampung	0	6	1	7	
19	Bangka Belitung	1	4	0	4	Fragmented from South Sumatera
21	Riau Islands	1	4	2	6	Fragmented from Riau
31	Jakarta	0	0	0	0	
32	West Java	0	1	4	5	
33	Central Java	0	0	0	0	
34	Yogyakarta	0	0	0	0	
35	East Java	0	0	1	1	
36	Banten	1	0	3	3	Fragmented from West Java
51	Bali	0	0	0	0	
52	West Nusa Tenggara	0	2	1	3	
53	East Nusa Tenggara	0	8	0	8	
61	West Kalimantan	0	6	1	7	
62	Central Kalimantan	0	8	0	8	
63	South Kalimantan	0	2	1	3	
64	East Kalimantan	0	6	1	7	
71	North Sulawesi	0	8	0	8	
72	Central Sulawesi	0	6	0	6	
73	South Sulawesi	0	3	1	4	
74	Southeast Sulawesi	0	6	1	7	
75	Gorontalo	1	4	0	4	Fragmented from North Sulawesi
76	West Sulawesi	1	2	0	2	Fragmented from South Sulawesi
81	Maluku	0	7	1	8	
82	North Maluku	1	5	2	7	Fragmented from Maluku
91	West Irian	1	7	1	8	Fragmented from Papua
94	Papua	0	22	0	22	
	Total	7	164	32	196	

Sources: Ministry of Home Affairs Republic of Indonesia *(Kementerian Dalam Negeri Republik Indonesia)*, (http://www.ditjen-otda.depdagri.go.id/index.php/data-otda/otda-2)

In the period from 1999 to 2009, the number of provinces increased by seven, from 26 to 33. Also, the number of regencies increased, by 164, from 235 to 399 or 66.8 percent. The number of cities also increased, by 34, from 64 to 98 or 53.1 percent. Overall the third-tier (regency/city) increased by 198 regions, from 299 to 497, or 66.2 percent. The fast regional fragmentation indicates a potential influence on the shifting of the concentration of economic activities specifically for manufacturing industries. From the policy perspective, it has also the potential power to contribute to the acceleration of industrialisation.

There are some interesting features related to this regional fragmentation. Firstly, the regional fragmentation took place largely outside of Java since the region is very spacious and it is conducive to fragmentation. The province with the highest fragmentation level during 1999 to 2009 is Papua, which has 22 new third-level tier regional governments, following by North Sumatera (14 new regions) and Aceh (13 new regions). Meanwhile, in Java there is no significant fragmentation of regions since Java has reached the optimum density levels. For example, East Java province has only one new region during that period, while Central Java, Yogyakarta and Jakarta have no new region. The only fragmented province in Java is West Java, in which Banten has fragmented as a new province.

The second aspect is that the fragmentation of districts is greater than that for cities or provinces. This trend is in accordance with the real condition in Indonesia where the regions with the status of "district/regency" dominate the geographical structure, more specifically for outside Java. In addition, Table 2.9 also describes that the regional fragmentation in Java mostly occurs at the city level. Seven new cities have been established during the period of 1999 to 2009. The emergence of new cities also shows that some regions experienced rapid economic development and social progress. Some regions emerged due to the spillovers effects from the centres of growth. The third aspect is that there are four provinces with no experience in fragmentation (i.e., Jakarta, Central Java, Yogyakarta and Bali). Those provinces have achieved an optimum level of density so there is only a little space for the establishment of new regions.

Following rapid industrialisation and regional fragmentation, some regions transformed into new potential industrial-bases. The emergence of potential regions is influenced by positive spillovers from their neighbours, which are regionally more developed. However, some new regions emerge as a result of being fragmented from an old region. Table 2.10 illustrates some emerging regions from 2000 to 2009 based on their contribution of value added, labour and number of firms to aggregate national industry. The district of Karawang is the region that has experienced the fastest industrialisation in this period. The national contribution to value added, labour and number of firms increases significantly from only 0.17%, 0.13% and 0.10% in 2000 to 3.93%, 2.45%, and 1.18%, respectively in 2009, respectively. Geographically, Karawang benefited from the accumulation of the development at Jakarta and its surrounding regions. As the closest region to Jakarta and Bekasi, Karawang experienced the shifting of production activities from both regions in response to increased density. Karawang also gained from the availability of transportation. Table 2.10 describes the leading industries responsible for accelerating industrial development in each region. In brief, Karawang receives optimum spillovers from Jakarta and its surrounding regions.

Table 2.10: Selected Emerging Regions at the District Level, 2000 to 2009

No	Region/District	Share to National Level (%)						Industrial Base	Growth Centre Nearest
		2000			2009				
		V	L	F	V	L	F		
1	Karawang	0.17	0.13	0.10	3.93	2.45	1.18	Paper and paper products (21), textiles (17), chemicals (24)	Jakarta
2	Pasuruan	1.36	1.90	1.80	1.80	2.33	2.85	Food and beverages (15), tobacco (16), textiles (17)	Surabaya
3	Ogan Ilir[1)]	0.00	0.00	0.00	1.31	0.07	0.10	Food and beverages (15), coal, refined petroleum and nuclear fuel (23), metal products except machinery and equipment (28)	Palembang
4	Batu Bara[2)]	0.00	0.00	0.00	0.43	0.12	0.20	Basic metals (27), Food and beverages (15), rubber and plastic product (25)	Medan
5	Cimahi	0.08	0.07	0.08	0.88	1.63	0.56	textiles (17), wearing apparel (18), chemicals (24)	Bandung
6	Sukabumi	0.02	0.14	0.12	0.36	1.53	1.18	Food and beverages (15), wearing apparel (18), radio, television and communication equipments (32)	Bogor

Note: V is value added; L is labour; and F is number of firms; [1)] fragmented from district of Ogan Komering Ilir in 2003; [2)] fragmented from district of Asahan in 2001.
Source: Large and Medium Industrial Statistics 2000 and 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Another region experiencing fast acceleration of industrial development is the district of Pasuruan in the province of East Java. Different from Karawang, which is located very close to Jakarta and Bekasi, the district of Pasuruan is located far from Surabaya as the centre of regional growth. However, many firms select this district as a basis of their production. The percentage of firms located in this region to total manufacturing increased from 1.8% in 2000 to 2.85% in 2009. The district of Sukabumi and Cimahi in West Java province has a similar pattern. Both regions receive positive spillovers due to the proximity to Bogor and Bandung as centres of regional growth. Outside of Java, the district of Ogan Ilir and Batu Bara emerge as new regions after being fragmented from the prime region. Both regions have growth potential due to the effects from the previous conditions, in which both regions are recognised as developed districts.

2.6. Manufacturing Development in the Framework of Long-term National Development Plans 2005–2025

As briefly discussed, the period of recovery and development of the manufacturing industry 2005–2009 is actually the first five years of the long-term industrial development program. It has been characterised by a decline in manufacturing growth and contribution to Gross Domestic Product (GDP).[5]

According to the blueprint of industrial development, the long-term manufacturing development policy is divided into two main periods: the medium-term development period of 2004–2009, which has passed, and the long-term development period of 2010–2025. The foremost goals in the period of 2010–2025 are strengthening the manufacturing basis to promote industry at the international level, strengthening the prime-mover industries, increasing the SMEs contribution to GDP, and strengthening the networks between SMEs and large industries.

To achieve these goals, the government has two integrated strategies. The first is a "grand strategy", which is focused on strengthening the linkage between industries in the same value chain. This involves increasing value added based on industrial core competencies, increasing productivity, efficiency, and resources allocation, and promoting SMEs' role in manufacturing industries. The second is an "operational strategy", which consists of:

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[5] Summarized from "Blueprint of National Industrial Development Policy 2005", published by the Ministry of Industry and Presidential Regulation 28/2008 on National Industrial Policy.

a) developing a sound business environment that includes institutional issues, infrastructure, credible industrial policies, law instruments and sectoral policies;

b) promoting prioritised industrial clusters as prime-movers. In the long-term period, the government will focus on the strengthening, deepening and development of clusters in five industry groups (i.e., agro-industry, transport equipment industry, information and technology-based industries, basic manufacturing industries, and particularly SMEs). By considering the special circumstances, in the period of 2004–2009, manufacturing development started in 10 clusters and is constituted as the core industry.[6];

c) determining the priority of the distribution of inter-regional manufacturing development to be close to the raw material resources, specifically for the industry located outside Java and low-industrial activities regions; and

d) developing innovation capabilities specifically for technology and management through research and development (R&D) activities.

In accordance with these strategies, the government also formulated the time frame for technological upgrading levels during the long-term industrial development program. In general, it consists of three main stages. The period of 2004–2009 is set up as the initiation stage, followed by the rapid development stage in 2010–2015 and the mature stage with technology upgrading in 2016–2025.

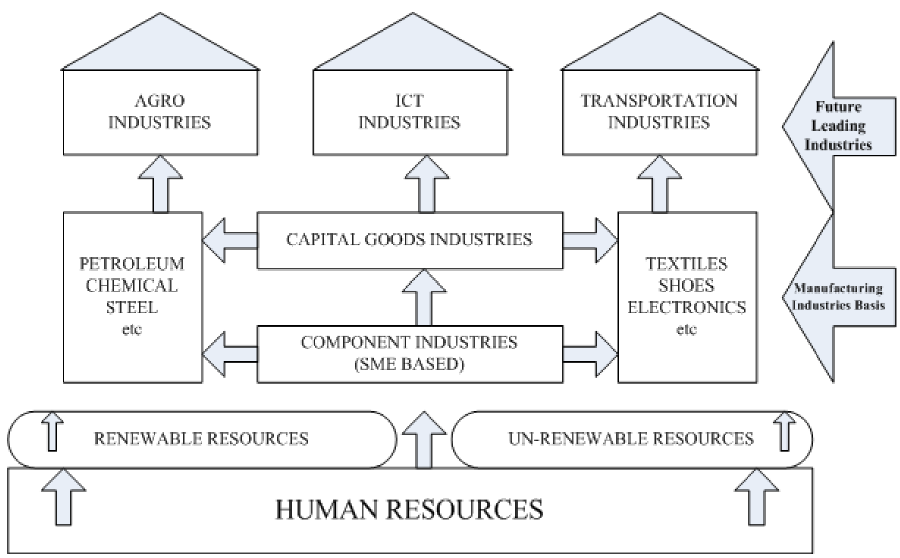
The policy action in each stage of industrial development depends on the characteristics and the existing conditions in each industry. For example, in the textile industry, as one of the leading sectors in the history of Indonesia's manufacturing development, this sector has actually passed the initiation stage prior to the period of 2005–2009. Consequently, the policy action in this industry is directed against the competition in the international market by improving technology and design for high fashion. On the other hand, unlike the textiles industry, the development of the bio-diesel industry should be initiated with a pilot project during the initiation stage (2005–2009) to search for indigenous technology as the basis for further production processes. Bio-diesel is a new product, which in Indonesia is derived from the palm oil industry.

[6] Food and beverages industry, manufactured marine-products industry, textiles and garments industry, footwear industry, palm oil industry, woods industry, rubber industry, pulp and paper industry, machinery and electricity industry, and petroleum industry.

To synchronise the entire industrial program into one integrated policy package, the government has introduced "A Model of Indonesian Industrial Structure 2025" as presented in Figure 2.9. This model explains the expected conditions in the manufacturing industry in the future. When reaching a mature stage, the manufacturing industry is expected to become the prime mover of the national economy and the source of national sufficiency. Moreover, it will establish deep inter-industry linkages, and vigorous competitiveness in the international market.

Figure 2.9 illustrates the inter-connection between national resources (human and natural) industries and the future leading industries, in which skilled labour, renewable natural resources and technology are expected to become the major foundation. To realise the industrial model, the government requires a set of strategies that are appropriate to its notion. Specialisation, spatial and industrial clusters are the core strategy. The arising geographical concentration of the manufacturing industry is a potential enabler for the specialisation and clusters approach, even though there remains a serious debate at the implementation level.

Figure 2.9: A Model of the Indonesian Industrial Structure 2025



Source: National Industrial Development Policy 2005, Ministry of Industry Republic of Indonesia.

2.7. Conclusion

This chapter provides an overview of manufacturing development in Indonesia, covering its structural transformation, stages of industrialisation, industrial policy and performance, and regional industrial development and agglomeration. It notes that Indonesia has undergone the structural transformation from the agriculture sector to manufacturing industry. Since the 1970s, Indonesia has passed through at least six major industrialisation stages, starting with open economic policies and prioritising the resources-based and labour-intensive industries, such as textiles and garments. During the oil boom period of 1973–1982, the industrial policy changes to being more closed and highly reliant on the SOEs. Until the middle of 1980s, the industrial strategy focused on import substitution (inward looking), while after the downturn in oil prices, the government implemented the export promotion (outward looking) strategy.

In 2001, the government initiated the "revitalisation program" to bring back growth to manufacturing industry by identifying problems and set up short-term actions to respond to the impact of the crisis. In 2005, "the national manufacturing development policy" launched in accordance with the Medium-term Development Program 2004–2009 and the Long-term National Development Program 2005–2025. The crucial challenge faced by the government is regional autonomy and the trend of regional fragmentation because of decentralisation. Regional autonomy has brought significant change in the pattern of economic geography since 2001. The delegation of authority from the central government to third-tier government (regency/city) requires industrial development policy based on the regional or spatial perspective.

Other important features considered include the emergence of spatial concentration or industrial agglomeration as impacts of national industrial development. Industrial agglomeration has received a great deal of attention from the government. In Indonesia, such agglomeration of economic activities is formed through a natural process due to the proximity of economic resources, access to markets, or access to services. Manufacturing industries tend to be spatially concentrated in the particular regions. Large provincial capitals, such as Jakarta, Surabaya and Bandung, together with their surrounding regions remain the centre of agglomeration, where most of the manufacturing companies are located. Some new regions, such as Karawang, Pasuruan, Sukabumi and Cimahi emerge due to the positive effect of spillovers from the nearest centres of growth. This spatial concentration phenomenon is important for future industrial development, since agglomeration is considered to provide positive effects to economic growth and productivity through its external economies. However, how agglomeration affects growth and productivity in the Indonesian manufacturing industry is still a phenomenon that needs to be investigated further. The extensive analysis of this issue is carried out in the next chapter, specifically on the compatibility of the theory and its implementation in Indonesia.

Chapter 3

Agglomeration, Productive Efficiency, and Productivity Growth: A Survey of the Literature

3.1 Introduction

Chapter 2 discusses the growth and performance of the manufacturing industry in Indonesia since the 1970s. One interesting feature of this growth concerns the tendency of firms to concentrate their locations within particular regions that have adequate access to markets, appropriate infrastructures and production inputs. In general, this tendency is known as agglomeration. Agglomeration is recognized as an important factor in economic development, especially for improving areas of economic performance such as productivity, innovation and economic growth. Ciccone (2002) states that increases in the agglomeration within particular regions positively affects regional growth. Similarly, Fujita and Thisse (2002) mention that agglomeration can be considered the territorial counterpart to economic growth

According to Marshall (1920), firms tend to concentrate in particular regions to obtain benefits from economies of scale, labour pooling and knowledge spillovers. Location proximity encourages the transmission of knowledge, reduces transportation costs and creates a more efficient labour market. Ohlin (1933) and Hoover (1948) expand on Marshall's concept of agglomeration economies by dividing them into localization economies and urbanization economies. The first pertains to the economies of a specialized economy or specialization phenomena, while the latter pertains to the economies of an urban region with a diversified economy. The concept of urbanization economies coincides with Jacobs' (1969) thoughts concerning knowledge spillovers, in which she argues that the diversity found in geographically concentrated industries stimulates innovation and growth. In addition, Porter (1990) provides more insight into the knowledge spillovers theory, where he suggests that competition rather than monopoly promotes innovation and growth.

This chapter reviews the existing literature on agglomeration, specifically focusing on the relationship between agglomeration economies and productivity growth and including relevant empirical evidence. The rest of this chapter is organized as follows. Section 3.2 defines the concept of agglomeration. Section 3.3 discusses the relationship between agglomeration economies and productivity growth, while Section 3.4 describes the concept of externalities and spillovers. Section 3.5 introduces the empirical evidence associated with agglomeration and productivity growth in both international and Indonesian studies. Section 3.6 concludes the chapter.

3.2 The Concept of Agglomeration

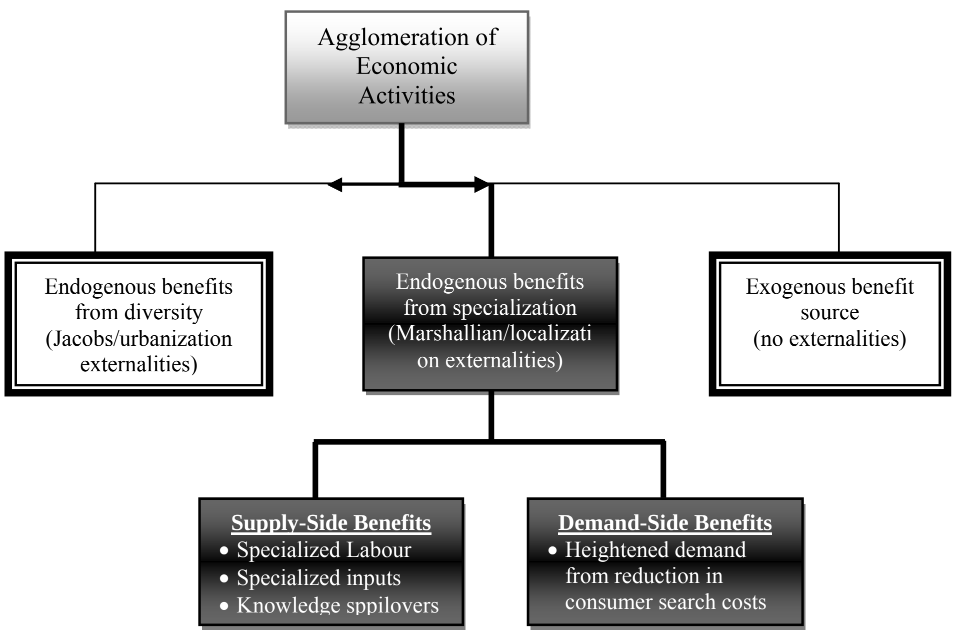
Ever since the term "industrial district" was first introduced by Marshall in 1890, the agglomeration model has received extensive attention from scholars, particularly from the 1950s through the 2000s (Maskell and Kebir 2006). [7] However, the term agglomeration is often used interchangeably with "specialization" or "concentration" (Nakamura and Paul 2009). Referring to Marshall's model, the centre of the agglomeration concept lies in the spatial concentration of economic activities. However, there is no scholarly agreement on a standard definition of agglomeration mentioned in the literature.

Wheeler et al. (1998) states that agglomeration refers to a geographic concentration of activities. According to Krugman (1991b), industrial agglomeration is formed from the existence of a demand linkage between firms, which is generated by the interaction of transportation costs and the fixed costs of production. Further, de Groot et al. (2009) explain that, historically, an agglomeration of economic activities emerges due to the efficient and strategic advantages of settling at particular locations that have access to available resources (such as water and landscape) and the interrelated development of the trading path. Brulhart (1998) argues that agglomeration typically refers to the spatial concentration of economic activities within a limited area, while spatial concentration applies to the spatial distribution of specific industries. In regards to the immobile and mobile factors involved, he differentiates between the definitions of agglomeration and specialization.

[7] Maskel and Kebir (2006) mention that during the 1953 to 2004 period, the number of articles published in scholarly journals within the social sciences with the term "cluster" and its synonyms is as follows: cluster(s)/clustering of firm(s) (24); agglomeration (759); geographic(al) agglomeration(s) (11); spatial agglomeration(s) (43); agglomeration(s) of (same industry) firm(s) (126); geographic(al) concentration(s) (86); spatial concentration(s) (69); localized industries/firms (12); growth pole (26); innovative milieu(s) (34); industrial district(s) (231).

The tendency of firms to concentrate within a specific region depends on the rationale of economic reasoning. As briefly mentioned in the introduction, Marshall (1920) identifies three sources of agglomeration economies: input sharing, labour market pooling, and knowledge spillovers. Agglomeration is also triggered by the cost of transportation (Krugman 1991b), the concentration of demand and natural advantage (Greenstone et al. 2008; Cohen and Paul 2009), local amenities (Greenstone et al. 2008), home market effects, and consumption and rent seeking (Rosenthal and Strange 2004). Hanson (2000) mentions that agglomeration occurs because companies benefit from being close to other companies in a particular industry. Firms benefit from agglomeration in terms of efficient access to necessary resources and improvement in the demand for goods and services (McCann and Folta 2008). The different streams of agglomeration from economic activities are schematically described in Figure 3.1.

Figure 3.1: Sources of the Agglomeration of Economic Activities



Source: McCann and Folta (2008)

3.3 Agglomeration and Productivity

Productivity advantages relating to the geographic concentration of industries such as agglomeration economies have become a major topic for discussion in the economic literature (Wheeler 2006). The concept of agglomeration economies is an important factor that encourages spatial concentration of economic activities; this concept has led to a large amount of research, particularly on the relationship between agglomeration economies and productivity (Rosenthal and Strange 2004). The fundamental question is whether agglomeration economies contribute to firm-level productivity.

Agglomeration economies are also recognized as location-specific economies. Following Marshall's (1920) theory, these economies are independent of any single firm but accrue to all firms located within the same area (McCann 2008). As mentioned in the introduction, Marshall initially provides three basic reasons why localized economies of scale exist: local knowledge spillovers, local non-traded input produced under scale economies, and local skilled labour pooling. McCann (2008) extends the insight from Marshall's theory by first mentioning that a spatially concentrated industry allows for frequent direct informal face-to-face contact between individuals that allows tacit knowledge to be shared between firms. Secondly, industrial clustering provides for the possibility that certain specialist input can be provided to the local group in a more efficient manner than would be the case if all of the firms were geographically dispersed. Thirdly, the spatial grouping of firms also allows for the creation of a local specialized labour pool, thereby reducing labour search and employment costs, and provides a risk reduction mechanism in the face of firm-specific demand fluctuations.

In reality, establishing a direct link with the Marshallian concepts can be very difficult. Following the theory proposed by Ohlin (1933) and Hoover (1937), agglomerations economies are classified into three types, namely —internal returns to scale, localization economies, and urbanization economies (McCann 2008). Localization economies refer to the agglomeration benefits that accrue based on activities within the same sector when they are located in the same place, whereas urbanization economies refer to agglomeration benefits that accrue based on a diverse range of local sectors. Recently, after the seminal work of Glaeser et al. (1992), most scholars have begun to refer to agglomeration economies as Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity), and Porter's externalities (or competition).

Theoretically, spatially concentrated industries can contribute to productivity through several mechanisms. For instance, these industries can contribute through growth such as that measured using the endogenous growth model proposed by Romer (1986), dynamic externalities (Glaeser et al. 1992), and innovation (McCann 2008). These concepts have been followed with substantial progress in mathematical and econometric modelling, which examine the link between agglomeration economies and productivity growth. The following sub-sections discuss the relevant models addressing the relationship between agglomeration economies, productivity and growth.

3.3.1 The Relationship between Agglomeration and Productivity

An empirical analysis of agglomeration economies typically involves characterizing one or more of their causes by utilizing proxies and relating these to the observed concentration of firms (Cohen and Paul 2009). One of the key debates relates to whether there is an absolute or a relative productivity impact in relation to agglomeration economies. Empirically, for example, Henderson (1986) and Nakamura (1985) analyse and compare the different impacts of localization economies and urbanization economies. Similarly, Henderson (2003) tests the Marshallian causes behind agglomeration economies. Several approaches are commonly applied to measure firm productivity through empirical analysis. According to Cohen and Paul (2009), one of the analyses focuses on the labour-demand shift in terms of employment and wages. For example, Glaeser et al. (1992) and Henderson et al. (1995) analyse the relationship between spatial industrial concentration and employment growth. These analyses are based on the assumption that enhanced productivity from agglomeration economies implies a greater demand for labour.

Cohen and Paul (2009) also emphasize that research on agglomeration economies involves direct modelling and measuring of productivity. However, many studies on the productivity effects of agglomeration tend to focus on only a single input — typically labour productivity. For example, Ciccone and Hall (1996) and Ciccone (2002) analyse the relationship between regional employment density and labour productivity growth. Most studies on agglomeration economies and productivity utilize production theory, regardless of whether it is applied in a single-input model or to multi-factor productivity.

As mentioned in Cohen and Paul (2009), one of the more significant models of agglomeration economies and productivity is proposed by Rosenthal and Strange (2004), involves augmenting a standard production function model such as:

$$y_j = g(A_j) f(x_j) \tag{3.1}$$

where j is firm, y_j denotes the value of the aggregate output, and the vector x_j includes the levels of the inputs commonly specified in production theory such as labour, capital, energy, and materials. In addition, $g(A_j)$ indicates the production function shifts from the environmental factors underlying agglomeration economies. In addition, Cohen and Paul (2009) state that this standard model is similar to the models of shifts $f(x_j)$ over time from technical changes, which are typically expressed in terms of a multiplicative factor $A(t)$ in microeconomic theory. However, the impact of distance is somewhat more complicated than that of time because space is not as readily defined.

In specific terms, Rosenthal and Strange (2004) write the above model A_j as $A_j = q(X_j, X_k) a(d^G_{jk}, d^I_{jk}, d^T_{jk})$, where k denotes the firms for which spillovers with other firms j occur. Cohen and Paul (2009) explain that $q(X_j, X_k)$ reflects externalities that depend on the input levels (and scale) of firms j and k and that $a(d^G_{jk}, d^I_{jk}, d^T_{jk})$ captures the different dimensions along which "distance" can be measured —spatial (*G*, geographic proximity, such as the same country or state), industrial (*I*, type of economic activity that confers externalities, such as own industry and suppliers), or temporal (*T*, the time dimension, such as learning with a lag). A_j can also accommodate factors of production, such as the local availability of primary materials or infrastructure, that perform as external inputs. In addition, A_j is commonly specified in terms of one or a limited number of less detailed proxies for agglomeration drivers such as a general measure of density or scale. For example, A_j captures factors such as number of population, employment, external spillovers or input.

In addition, Cohen and Paul (2009) explain that the multiplicative form of A_j in Equation (3.1) imposes a neutrality of the productivity effect, or the separability of the 'input' in x_j and A_j, which is apparent in most of the literature and supported by

Henderson (1986). However, if the factors in A_j have differential or non-neutral input effects (Cohen and Paul 2009), A_j or possibly a set of the agglomeration causes or factors in A_j should be included directly as asserts of the production function:

$$y_j=f(x_j,A_j) \quad (3.2)$$

If $f(.)$ in Equation (3.2) is in a flexible functional form, such as a translog (second-order approximation in logarithms) or generalized Leontief (second-order approximation in square roots), this function captures the dependence of the x_j marginal products on both input levels and A_j variables either in the form of interaction effects or cross effects.

As noted by Cohen and Paul (2009), a single input demand model is theoretically related to a production function as indicated in Equation (3.2), because the increase in overall productivity from A_j factors implies the greater marginal productivity or value of, and thus demand for, the input in x_j. However, a full production function model, particularly when it is specified without the neutrality assumptions imposed and approximated to the second order recognizes both substitutability among inputs and input-specific shift effects. Furthermore, in such model, the relationship between agglomeration economies and firm productivity is more direct because of the A_j factors that directly increase the marginal products of inputs, indirectly transform into higher wages level (or values of asset) and employment (or investment).

3.3.2 The Relationship between Agglomeration and Growth

Existing theories and empirical evidence suggest that the regional concentration of economic activities stimulates growth (Glaeser et al. 1992; Henderson et al. 1995). As long as economies of scale, knowledge spillovers and a local pool of skilled labour result in productivity benefits that compensate for congestion or density costs, the economy will benefit from agglomeration, at least in terms of efficiency and growth (Martin et al. 2011).

One of the most recognized frameworks for growth and agglomeration is proposed by Glaeser, et al. (1992) and has recently been widely utilized by scholars. Traditional theories have view the externalities associated with knowledge spillovers as the engine of growth (Ueki 2007). Glaeser et al. (1992) hypothesize that geographical proximity is a key factor in facilitating the transmission of ideas and growth within cities. As explained by de Groot et al. (2009), the model of Glaeser et al. (1992) is based on a simple neoclassical model describing economic functioning.

The key to the Glaeser et al. (1992) approach is the production function, using technology *(A)* and labour *(l)* as input. The model assumes perfect competition where the profit-maximization of individual firms results in an equality of the product marginal value and wage rate. Moreover, de Groot et al. (2009) explain that, based on a simple Cobb-Douglas production function $y_{irt}=A_{irt}l_{irt}^{1-\alpha}$ (with *i* and *r* referring to industry and region respectively), one arrives at the labour demand function:

$$l_{irt}=\left(\frac{\alpha A_{irt}}{w_{irt}}\right)^{\frac{1}{\alpha}} \tag{3.3}$$

By taking logs on both sides, the expression of growth rates is obtained:

$$\alpha log\left(\frac{l_{irt+1}}{l_{irt}}\right)=log\left(\frac{A_{irt+1}}{A_{irt}}\right)-log\left(\frac{w_{irt+1}}{w_{irt}}\right) \tag{3.4}$$

The above equation clearly indicates that the growth rate of employment – *ceteris paribus* – depends positively on the state of technology growth and depends negatively on the growth rate of wages. Subsequently, the growth rate of technology is assumed to be dependent on national and local components. Consistent with this argument, Ueki (2007) asserts that the growth of national technology in the model of Glaeser et al. (1992) is assumed to capture changes in the price of the product as well as shifts in national technology within the industry. However, local technology is assumed to grow at a rate exogenous to the firm while depending on the various technological externalities within the city that are present in the industry. There are three type of externalities identified that relate to this relation, namely, specialization, competition, and diversity. The equation for this is as follows:

$$log\left(\frac{A_{irt+1}}{A_{irt}}\right)=log\left(\frac{A_{it+1,national}}{A_{it,national}}\right)+g(specialization,\ competition,\ diversity) \tag{3.5}$$

If we substitute Equation (3.5) into Equation (3.4), the equation becomes

$$\log\left(\frac{l_{ir,t+1}}{l_{irt}}\right)=-\frac{1}{\alpha}\log\left(\frac{w_{ir,t+1}}{w_{irt}}\right)+\frac{1}{\alpha}\log\left(\frac{A_{i,t+1,national}}{A_{i,t,national}}\right)+\frac{1}{\alpha}g(specialization,\ competition,\ diversity) \quad (3.6)$$

In relation to Equation (3.6), de Groot et al. (2009) further explain that the wage growth term is constant in the regressions (i.e., real wages grow equally across industries and regions) and that changes in nationwide technology (and prices) are congruent with growth in nationwide industrial employment.

3.4 The Concept of Externalities and Spillovers

According to the economic growth theory as advanced by Romer (1986) and Lucas (1988), it has been argued that the externalities created by the interaction of economic agents are sources of productivity. This observation agrees with the concept of agglomeration economies, where the externalities created from the interaction between firms in close proximity ultimately improve firm-level productivity. In general, externalities are defined as the effects that spread from one activity and have an impact on another activity. However, this condition is not directly reflected within market price mechanisms (Griliches 1992; Beaudry and Schiffauerova 2009). Within the context of spatial concentration, numerous studies, such as Glaeser et al. (1992), Henderson et al. (1995), Feser (2002), and Ellison et al. (2007), mention that the advantages from agglomeration economies for the local economy or industrial development are explained by the concept of static and dynamic externalities.

Static externalities refer to specific benefits for firms from agglomeration within a single industry, recognized as localization economies, and benefits from urban scale and diversity or urbanization economies. According to Marshall (1920), these externalities are primarily stimulated by access to natural resources, transportation advantages, and cost savings from moving inputs. Conversely, dynamic externalities such as knowledge spillovers and learning by doing arise primarily from the dynamic interaction process between firms and/or labour. The accumulation process of dynamic externalities then contributes towards increasing productivity levels and employment (Henderson et al. 1995). Scholars have widely considered dynamic externalities to be a source of agglomeration economies. As mentioned before, Glaeser et al. (1992) propose three terminologies for dynamic externalities, namely

Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity), and Porter's externalities (or competition).

3.4.1 Marshall-Arrow-Romer (MAR) Externalities

According to Glaeser et al. (1992), MAR externalities address knowledge spillovers between firms within a particular industry, which originally refers to Marshall's concept concerning an industrial district. Arrow (1962) extends this concept with some formalization and Romer (1986) provides influential views that are specifically related to knowledge spillovers as an engine of growth. The MAR theory stresses the benefits of knowledge spillovers within an industry, where knowledge accumulated from a sustainable interaction process tends to assist the technological development of other firms without appropriate compensation. This process is realized within a geographically concentrated industry, where the producers can learn from each other's experiences through inter-firms labour communication and movements. Moreover, firm proximity within a specific region facilitates uncomplicated and free information transmission, so that industries that are spatially concentrated and benefiting from within-industry knowledge transmission should grow quickly. As a result, the regions with such industries should also grow faster than other regions (Glaeser et al. 1992). This finding indicates that, based on the MAR concept, local monopoly or specialization is useful for accelerating economic growth because it allows for the internalization of externalities (Romer 1990).

3.4.2 Jacobs' Externalities

Jacobs' externalities focus on industrial diversity as a source of growth because a greater exchange of ideas between firms in different industries will promote innovation and growth (Glaeser et al. 1992). Jacobs (1969) argues that the most prominent sources of knowledge spillovers are those resulting from interactions between firms from different industries within a particular region. She emphasizes that a variety of industries within a specific region promotes knowledge spillovers and innovative activity (Beaudry and Schiffauerova 2009), so that diversity stimulates the transmission of knowledge externalities and innovation, leading to economic growth (Henderson et al. 1995). A more diverse industrial environment based on spatial proximity encourages the process of inter-industry idea sharing, imitation, and practicing (Beaudry and Schiffauerova 2009). In conjunction with these benefits, Harrison et al. (1996) state that a more diverse economy is suitable for exchanging skills and knowledge, thus giving rise to new industrial fields. In addition, as far as local monopoly and competition are concerned, Jacobs supports competition as a driving factor for innovation. She argues that a monopoly unreasonably harms cities or regions and restrains their economies from achieving at their potential (Glaeser et al. 1992); therefore, an industry that is located within a more diversified regions should grow faster, leading to a diversified economy (Quigley 1998).

3.4.3 Porter's Externalities

Porter's externalities focus on the role of competition within local economic or industrial growth. Like MAR's model, Porter agrees with the contribution of specialization toward the growth of both specialized industries and/or the region they are located in or from spillovers from firms within the same industry (Glaeser et al. 1992). Porter states that knowledge spillovers mostly occur in vertically-integrated industries, agreeing with the Marshallian specialization hypothesis (Beaudry and Schiffauerova 2009). Conversely, concerning the innovation process, Porter agrees with Jacobs that local competition is good because it supports imitation and innovation. Moreover, Porter argues that strong competition leads to innovation and accelerates technical progress, thereby leading to growth in productivity levels. This argument is different from MAR's model, which argues that a monopoly is useful because it allows for the internalization of externalities.

Empirically, the question of whether diversity or the specialization of economic activities is better for promoting technological change and economic growth has been the subject of heated debate in the economic literature (Beaudry and Schiffauerova 2009). Table 3.1 shows the summary of the sources for spillovers with regard to these aspects.

Table 3.1: Sources of Spillovers

	MAR	Jacobs	Porter
Specialization	+	-	+
Diversity	-	+	-
Competition	-	-	+

Source: Beaudry and Schiffauerova (2009).

3.5 Agglomeration Economies and Productivity Growth: Empirical Evidence

A large number of studies provide empirical evidence concerning the contribution of agglomeration economies to regional economic performance. The term “regional” can be defined as a formal state region, city, or specific local industrial concentration. Generally, the measurement indicators are represented by productivity growth, economic growth, innovation, and industry behaviour (Hanson 2000). In accordance with these studies, Beaudry and Schiffauerova (2009) conduct a meta-analysis of agglomeration economies by comparing the roles of specialization (Marshallian externalities) and diversity (Jacobs’ externalities) in economic performance.

In their review, Beaudry and Schiffauerova (2009) classify the performance measures of a region and firm into three main categories: economic growth, productivity and innovation. Most of the studies that focus on analysing the relationship between agglomeration economies and economic growth use employment growth as a proxy indicator. Other measures that are often included in the analysis are the number of new firms, wage growth, plant size, number of employees per firm, and the number of plants or the number of employees per area.

Several proxy variables are used in studies that analyse the effects of agglomeration economies on productivity growth. These variables include output per labour hour, total production factors, value-added growth, efficiency scores and ability to export. The most common measure used is firm output. When the data for capital stocks are available in a time series, total factor productivity (TFP) growth can be measured. Beaudry and Schiffauerova (2009) explain that productivity-based measures are theoretically closer to the concept of dynamic externalities and are an improvement over employment-based measures. Recent studies on the relationship between agglomeration economies and productivity growth have been mostly conducted using firm-level data, such as those performed by Henderson (2003), Feser (2002), and Kuncoro (2009).

Finally, the studies that focus on examining agglomeration economies and innovation generally use the number of patents as a proxy for innovative output. Other indicators used in this analysis are the number of inventions reported by trade journals, R&D intensity, and the likelihood of adopting a particular innovation, the number of innovators, and the innovativeness or the economic impact of an innovation after two years. Beaudry and Schiffauerova (2009) explain that patents have long been used as indicators of innovation because they are closely related to innovativeness and based on a slowly changing standard. Patent information is also easily accessible and widely covered.

In general, results indicate a pattern that corroborates with the theory. However, several studies indicate a different direction and mix. The different results are related to the methodology or approach used in the research, the definition and formulation of the indicators, and the scope of the industries or the regions. Scholars tend to differ in their opinions regarding the appropriate measurement for the indicators used to represent economic growth or productivity growth. Beaudry and Schiffauerova (2009) state that there should be a distinction between the various agglomeration economies that affect economic growth and productivity growth. The following sub-sections describe the empirical evidence regarding those issues from two perspectives: international case studies and Indonesian case studies.

3.5.1 International Studies

Empirical analyses of the relationship between agglomeration economies and productivity growth start in the 1970s and are followed by rapid progress in the development of theoretical and empirical approaches (Feser 1998). Various studies reveal that agglomeration economies stimulate firm productivity and improve regional economic performance (Koo 2005). The following analysis discusses those studies addressing the effect of agglomeration economies on productivity growth based on different perspectives, approaches and measurements. The term "productivity" follows the definition provided by Beaudry and Schiffauerova (2009), as is discussed in the previous sub-section. An analysis of the empirical studies on agglomeration economies is focused on the period after the seminal work of Glaeser et al. (1992).

In spite of extensive studies on agglomeration economies, only a few have analysed the relationship between agglomeration economies and total factor productivity (TFP) growth. Deckle (2002) estimates the impact of dynamic externalities (MAR, Jacobs' and Porter's externalities) on TFP growth and employment growth at the regional level in Japanese prefectures. The results for one-digit industry level show no dynamic externalities of any type in manufacturing. However, strong MAR externalities are found in the finance sector (though no Jacobs' or Porter's externalities are found). Relatively strong MAR externalities (non-existent Jacobs' externalities and some Porter's externalities) are also found in the service industry and the wholesale and retail trade industry. For the pooled-estimation results, there is evidence of MAR and Porter's externalities, but no evidence of Jacobs' externalities.

Similarly, Cingano and Chivardi (2004) estimate the effects of alternative sources of dynamic externalities at the local level in Italy. The result is similar to Deckle (2002), where industrial specialization (MAR externalities) and scale indicators affect TFP growth positively but not employment growth. Neither study finds that Jacobs' externalities influence productivity growth. In addition,

Henderson (2003) estimates the effect of agglomeration externalities (MAR and Jacobs' externalities) on firm-level productivity growth by applying a panel data model in the high-tech and capital goods industries within the United States. The results reveal that locally owned industries' externalities have strong productivity effects in high-tech but not in machinery industries. For the firms in machinery industries, the externalities are too concentrated in their own counties so that there are no external benefits from other counties within the same region. Meanwhile, the Jacobs' externalities do not show up in any industries. The results also reveal the relationship between the level of agglomeration and the degree of scale economies.

More recently, Lin et al. (2011) examine the impact of agglomeration externalities on firm productivity growth within the textile industry in China. They find that agglomeration economies have a positive but nonlinear relationship with firm-level productivity. Agarwalla (2011) investigates the relationship between agglomeration economies and productivity growth within India. Using a growth accounting framework for 25 states over 27 years and across four sectors, the results support the hypothesis that urbanization economies tend to be very prominent across sectors. However, localization economies are not present in certain sectors, specifically in service-based industries. Further, Andersoon and Lööf (2011) examine the effect of agglomeration on labour productivity in the manufacturing industries within Sweden. They find a positive effect from agglomeration economies on firm productivity.

Graham and Kim (2008) confirm the positive elasticity of production with respect to agglomeration in United Kingdom manufacturing industries.

As mentioned by Beaudry and Schiffauerova (2009), studies on the relationship between agglomeration economies and productivity growth primarily utilize firm output as the proxy for productivity. Nakamura (1985) and Henderson (1986) apply the production function to examine the level of productivity and compare it under two different conditions. The first condition is when the regional own-industry scale is high, and the second is when the regional population is high. Using Japanese manufacturing industries, Nakamura discovers that the value added per-worker in Japanese cities increases with the scale of local industry output for most industrially produced capital goods but increases only a little for the industries that produced consumer or intermediate goods. However, Henderson finds that the output per-worker increases within local industry employment for the capital goods industries for Brazilian cities and for capital and consumer goods industries for United States cities.

Following Henderson (1986), Wheeler (2006) examines the role of plant scale with productivity and geographic concentration. Using two and three digit United States manufacturing industries between 1980 and 1990, the results indicate that the level of industrial employment within cities is strongly correlated with the average size of plants in the market and that there is a positive association between a worker's wage and the total employment in the city and industry.

Gao (2004) estimates the impact of dynamic externalities on regional industrial growth for 32 two-digit industries within 29 provinces in China. The results indicate that dynamic externalities (MAR, Jacobs' and Porter's externalities) positively influence regional industrial growth.

Lucio et al. (2002) examine the role of externalities in promoting productivity growth within Spanish regions. Using 26 manufacturing sectors from 1978 to 1992 across 50 provinces, they compare technological spillovers from outside of the industry (Jacobs' externalities) with those generated within the industry (MAR externalities). The study finds that specialization has a positive effect on productivity growth, but there is no evidence regarding diversity and competition. This result is similar to the previous study conducted by Henderson et al. (2001), which finds that the MAR externalities have a significant impact on the productivity of manufacturing industries within Korea from 1983 to 1993. Similar evidence is also found for Jacobs' externalities. However, when using the city's population as a measure of urbanization, the study found no evidence of externalities in these same industries.

Capello (2002) analyses the role of dynamic externalities on productivity growth in the high-tech industry in Milan, Italy. The results indicate that specialization plays a more important role than urbanization economies. Other findings reveal that localization economies have a positive impact on small firms, while urbanization economies are more advantageous for large firms.

Regarding empirical studies on the effect of agglomeration economies on economic and productivity growth, Beaudry and Schiffauerova (2009) summarize 67 peer-reviewed articles and find that 70% of these studies indicate the existence of MAR externalities that impact economic growth and innovative output, while 75% of them confirm the existence of Jacobs' externalities within a region. Approximately half of these studies support the theory with positive results, while the rest report concurrently positive and negative or non-significant results for the different industries, time-periods, countries or dependent variables used in the estimation model.

In addition to productivity growth, studies of agglomeration economies are linked to agglomeration's effect on economic growth. In this case, scholars most frequently use employment growth as the proxy variable for economic growth. Glaeser et al. (1992) examine the effect of agglomeration economies on growth using data sets on geographic concentration and competition for industries within 170 of the largest U.S. cities. The study focuses on the largest industries because in the growth model externalities are sources of permanent income growth. The results show that local competition and urban variety encourage employment growth, while regional specialization does not. The evidence also suggests that knowledge spillovers occur between industries, rather than within industries, consistent with Jacobs' theory.

Similarly, Henderson et al. (1995) use eight US manufacturing industries in 1970 and 1987 to examine production externalities within cities. They find evidence of MAR externalities that are associated with previously owned industry employment, and Jacobs' externalities that are associated with local diversity. In the case of mature capital goods industries, these authors find MAR externalities, but no Jacobs' externalities. New high-tech industries evidenced both MAR and Jacobs' externalities. These findings are consistent with the theory of urban specialization and product life cycles.

Likewise, Dumais et al. (2002) test the effect of agglomeration and employment changes within US cities in five-year intervals between 1972 and 1992. The study examines the relative stability of geographic concentration based on the dynamic process. The results indicate that the location selection of newly emerging firms and the differences in growth levels contribute significantly to reducing the degree of geographic concentration, while firm closures have a tendency to strengthen agglomeration.

Batisse (2002) examines the local economic structure (local sectoral specialization, diversity, and competition) and growth of Chinese provinces during 1988–1994 considering 29 industries. This econometric analysis shows that diversity and competition positively influence local growth, while specialization has a negative effect. He also finds that the industries located in coastal and interior provinces are subjected to different growth impulses. This finding is similar to the previous study conducted by Combes (2000) concerning 52 industries and 341 local areas in France. Combes finds a different impact from dynamic externalities in industry and services. In general, specialization and diversity both have a negative impact on growth; only a few industries see a positive impact.

Along with economic growth and productivity growth, agglomeration economies are also associated with technology and the firms' innovation levels. Technology spillovers and agglomeration are important factors in economic development because inter-firm technology exchange in geographically concentrated industries provides innovation incentives to firms. The agglomeration of firms facilitates localized spillovers through local innovation networks (Koo 2005). In the model concerning technological externalities, inter-firm information spillovers provide incentives for the agglomeration of economic activities (Lall et al. 2004).

Feser (2001) tests the economies of industry and urban size in two different technology intense industries in United States manufacturing by applying the framework of Kim's inverse input demand function. The findings indicate the presence of urbanization economies in moderate to low-technology industries (the farm and garden machinery sector) and localization economies in higher technology industries (the measuring and controlling devices sector). Kim's methodology permits a highly flexible and attractive test on urbanization and localization economies.

Ellison et al. (2007) examine the causes of industry agglomeration using a co-agglomeration pattern in US manufacturing industries from 1972 to 1997. The regression results of co-agglomeration on Marshall's factors of agglomeration reveal that lower transportation costs, labour market pooling, and knowledge spillovers support agglomeration. Table 3.2 provides brief summaries of the empirical studies on agglomeration economies and productivity growth.

Table 3.2: A Summary of the Selected Empirical Studies on Agglomeration Economies and Productivity Growth

No	Author(s)	Countries	Data	Coverage	Variables	Finding
1.	Deckle (2002)	Japan	1975 and 1995	9 manufacturing industries; 47 regional level	TFP growth	• One-digit industry level: different impact of MAR, Jacobs' and Porter's externalities. • Pooled: positive effect from MAR and Porter's externalities; no evidence of Jacobs' externalities
2.	Cingano and Chivardi (2004)	Italy	1991	10 manufacturing industries; 784 local labour systems (LLS);	TFP growth	Positive effect from MAR and Porter's externalities; no evidence of Jacobs' externalities
3.	Henderson (2003)	USA	1972–1992	5 three-digit manufacturing industries; 742 counties in 317 metropolitan areas	TFP growth	Positive effect from MAR (high tech industry) No evidence of Jacobs' externalities
4.	Lin et al. (2010)	China	2000–2005	Textile industry	TFP growth	Positive effect from agglomeration economies; nonlinear relationship with firm productivity
5.	Agarwalla (2011)	India	1980–2007	4 industry sectors; 25 states	TFP growth	Positive effect from urbanization economies and diversity; no localization effect
6.	Henderson (1986)	USA	1972	15 Manufacturing industries; 238 regions.	Firm productivity	Positive effect from localization economies; positive and negative sectoral impact of urbanization

No	Author(s)	Countries	Data	Coverage	Variables	Finding
7.	Henderson (1986)	Brazil	1970	11 manufacturing industries; 126 urban regions	Firm productivity	Positive effect from localization economies;
8.	Wheeler (2006)	USA	1980 and 1990	Manufacturing industries	Firm productivity	Positive effect from size and wage level
9.	Gao (2004)	China	1985–1993	32 two-digit industries; 29 regions	Industry growth	Positive effect from dynamic externalities
10.	Lucio et al. (2002)	Spain	1978–1992	26 manufacturing industries; 50 provinces	Firm productivity	Positive effect of specialization; no effect from diversity and competition
11.	Henderson et al. (2001)	Korea	1983–1993	23 two-digit manufacturing industries;	Firm productivity	Positive effect from MAR externalities; no evidence of Jacobs' externalities
12.	Capello (2002)	Italy	1996	133 firms; 2 regions	Firm productivity	Positive effect from localization and urbanization economies;
13.	Glaeser et al. (1992)	USA	1987	459 four-digit manufacturing industries; 170 largest cities	Employment growth	Positive effect from competition and urbanization; no evidence of localization
14.	Henderson et al. (1995)	USA	1970 and 1987	8 manufacturing industries; various cities	Employment growth	Positive effect from MAR and Jacobs externalities
15.	Henderson (1999)	USA	1963–1992	machinery and high-	Output growth	Positive effect from specialization

No	Author(s)	Countries	Data	Coverage	Variables	Finding
				tech industries		
16.	Batisse (2002)	China	1988–1994	29 manufacturing industries; Chinese provinces	Output growth	Positive impact from diversity and competition; negative impact from specialization
17.	Combes (2000)	French	1984–1993	52 industries; 341 local regions	Employment growth	Negative impact from specialization and diversity
18.	Andersoon and Lööf (2011)	Sweden	1997–2004	Manufacturing industries	Firm productivity	Positive effect from agglomeration economies (specialization)
19.	Mukkala (2004)	Finland	1995–1999	3 manufacturing industries; Finnish regions	Firm productivity	Positive effect from specialization and urbanization economies
20.	Feser (2001)	USA		Manufacturing industries	Technology intensity	• The presence of urbanization economies in moderate to low-technology industries. • The presence of localization economies in higher technology industries.

Source: Author's compilation

de Groot et al. (2009) provide a meta-analysis of the existing studies on the effect of agglomeration economies on productivity and economic growth. This meta-analysis offers a useful toolkit for seeing the variation in outcomes of the empirical studies. The results of the meta-analysis are provided in Table 3.3.

Table 3.3: A Summary of a Meta-analysis of the Studies on Agglomeration Economies, Economic Growth and Productivity Growth

	Specialization		Competition		Diversity	
	count	**%**	**count**	**%**	**count**	**%**
Negative significant	60	37	16	20	17	11
Negative insignificant	33	20	13	16	40	26
Positive insignificant	16	10	19	24	37	24
Positive significant	53	33	31	39	58	38
Total	162	100	79	100	152	100

Source: de Groot et al. (2009)

The results of the meta-analysis of de Groot et al. (2009) provide several important insights into agglomeration economies and productivity growth. There is no clear-cut evidence in the literature regarding the impact of specialization on urban growth. Although 70% of the available estimates are statistically significant, about half of those results are negative. Regarding competition, the results are somewhat clearer. Based on Table 3.3, 60% of the estimated effects measurements are statistically significant and approximately two-thirds of these are positive, which corroborates Porter's hypothesis on the importance of competition in promoting urban growth. Regarding the effects of diversity, only 50% of the estimates are statistically significant. Of those, however, over 75% point to the positive effects from diversity on urban growth.

3.5.2 Indonesian Studies

Although a large number of international studies concerning the effect of agglomeration economies upon productivity and economic growth are available, there are only a few studies related to this issue that use an Indonesian perspective. Most of the studies on the effect of agglomeration economies upon productivity growth in Indonesia focus only on specific manufacturing industries.

The empirical study performed by Henderson and Kuncoro (1996) is the first analysis of agglomeration economies in Indonesia and it then inspired subsequent studies on this issue. Using an econometric approach, this research investigates the factors that influence a firm's choice of location and the impact of the liberalization policy introduced by the government in 1983. The important finding is that a firm's decision regarding its location is influenced by several factors, including low wages, good infrastructure, a large market, the existence of mature firms, governmental roles and other services. Moreover, new firms tend to choose a location near more mature firms due to the benefits of knowledge spillovers, because the mature firms are normally better informed about the local market conditions, institutions and technology.

With a different focus and using firm-level data from selected Indonesian manufacturing industries, Kuncoro (2009) examines how concentration occurs as an economy becomes more developed. He also investigates how public policy mitigates emerging problems by supporting infrastructure development in less urban regions to encourage industries to concentrate in smaller cities. The approach used in this study involves firm productivity as a function of local industry inputs and external environments that generate spillovers, similar to Henderson et al. (2003).

The estimating equation in Kuncoro (2009) for assessing local externalities is based on a firm production function with constant returns to scale technology. The estimation uses the log-linear form of technology, assuming city, time, and individual fixed effects. Other variables introduced in this model are firm characteristics, such as legal status, firm ownership, and the age of the firm to control the shift in the production function due to individual effects. The results indicate that localization is stronger than the urbanization effect. Externalities exist in the form of localization, and smaller cities tend to specialize in only one industry or in closely connected industries.

Deichman et al. (2005) analyse the relationship between agglomeration, transportation, and regional development in Indonesia. Their study focuses on the aggregate and sectoral geographic concentration of manufacturing industries and estimates the impact of factors that influence a firm's location choice. The study assumes that a firm will respond to a combination of productivity, which enhances agglomeration economies, and the local characteristics that determine the "business environment" within a specific region. The findings suggest that an improvement in transportation infrastructure has a limited effect in attracting industries to secondary industrial centres outside of Java, especially in the sectors already established within the leading regions. The findings underscore the challenges of addressing industrial fortunes within lagging regions either through local decentralized policy interventions or through national policies focused on infrastructure development.

Like Ellison et al. (2007), Arhansya (2010) examines co-locations between firms in different industries. This approach is superior to others because it provides more information rather than investigating firms only at the industry level. The findings indicate that the role of Marshallian externalities is equally important as the shared natural advantages when forming spatial concentrations in Indonesia. Labour pooling, in this case, has the largest effect, followed by input-output relationships. Meanwhile, technology spillovers also have a significant influence, albeit relatively minor.

Kuncoro and Wahyuni (2009) examine the geographic concentration of manufacturing industries in Java, specifically the impacts of foreign direct investment (FDI) on industrial agglomeration, by comparing the three main theories: the neo-classical theory (NCT), new trade theory (NTT), and the new economic geography (NEG). The geographic concentration of manufacturing industries is measured by a regional specialization index. The results show that the NTT and the NEG are more important to explaining the phenomena of geographic concentration than the NCT. The manufacturing firms in Java tend to locate in areas that are more populous to benefit from both localization and urbanization economies. The results also suggest the existence of a synergy between the market's depth and agglomeration forces.

Irawan (2011) investigates the spatial distribution of large and medium manufacturing industries in the East Java province of Indonesia. The study focuses on analysing the degree of localization and co-localization, the randomness of observed localization, and the industrial structure of cities. Using a similar method to those used in the other studies, the results indicate a common nature in the study of agglomeration, most notably, the impact of scale economies.

Narjoko (2010) examines the industrial agglomeration within Indonesia. Econometric estimation and surveys are implemented. The results indicate that the most important factors for establishing business are the infrastructure and supporting activities, the availability of skilled labour and professionals, and the size of the domestic market. These results are consistent with previous studies. The findings support the "flowchart approach" of industrial agglomeration. The incentive for investment is another important factor for industrial agglomeration in Indonesia. The econometric analysis finds that technology transfer occurs from the industrial agglomeration process. Table 3.4 below shows the summary of studies related to agglomeration economies, economic growth and productivity growth in Indonesia.

Table 3.4: A Summary of the Selected Empirical Studies on Agglomeration in Indonesia

No	Authors	Period of Data	Coverage	Method/approach	Key Finding
1	Henderson and Kuncoro (1986)	1980–1985	Manufacturing industry (unincorporated sector) Java	Logit model	Plants strongly prefer locations with mature plants in related industries
2	Kuncoro (2009)	1990–2003	Manufacturing industry (Java)	Panel data	• Localization effects are stronger than urbanization effects • Smaller cities tend to concentrate in only one industry (case localization externalities) • Industry must find a location in a diverse, large urban environment (case urbanization externalities)
3.	Deichman et al. (2005)	1996–2001	Aggregate and sectoral manufacturing industries (Indonesia)	Panel data	Improvements in transportation infrastructure may have limited effects in attracting industry to secondary industrial centres outside of Java
4.	Arhansya (2010)	1991–2000	Manufacturing industry (Indonesia)	EG agglomeration index and regression	Marshallian externalities have an equally important roles as the shared natural advantages in the formation of spatial concentration in Indonesia
5.	Kuncoro and Wahyuni (2009)	1992–2002	Manufacturing industry (Java)	Panel data	new trade theory (NTT) and new economic geography (NEG) are more accurate for explaining the phenomena of

No	Authors	Period of Data	Coverage	Method/approach	Key Finding
					geographic concentration compare to the Neo-Classical Theory (NCT).
6.	Irawan (2011)	2002	Manufacturing industry (East Java Province)	OLS and 2SLS	The results commonly match with the study on agglomeration in Indonesia, most notably the impact of scale economies.
7.	Nardjoko (2010)	Various years	Manufacturing industry (Indonesia)	Econometric and survey	• The most important factors for establishing business are infrastructures and supporting activities, the availability of skilled labour and professionals, and the size of the domestic market. • The finding supports the "flowchart approach" of industrial agglomeration.
8.	Irawati (2008)	Various years	Cluster of automotive industries	Descriptive-analytic	The general spatial-economic conditions and cluster specific conditions need to be improved with regard to the organizing capacity.
9.	World Bank (2012)	Various years	Selected manufacturing industry	Panel data	Localization effects are stronger than urbanization effects.

Source: Author's compilation

In accordance with the discussion above, there are also studies analysing firm productivity growth in the Indonesian manufacturing industry that are not directly related to the analysis of agglomeration economies. A wide range of approaches is used in these studies. The findings vary, without any identifiable pattern. The following discussion reviews several of the important empirical studies on productivity growth in Indonesia.

Using a growth accounting model, Aswicahyono et al. (1996) estimates the total factor productivity growth in the manufacturing industry for the periods of 1976–1981, 1981–1985, and 1986–1991, finding TFP growth rates of 0.7%, 1.1%, and 2.6% for those periods, respectively. In addition, Timmer (1999) estimates the TFP growth for large and medium manufacturing industries for the 1975–1995 period. The results show that 60% of the growth in manufacturing output during this period is due to capital input growth, 18% to labour input growth and the remaining 22% to TFP growth. The average TFP growth is 3% annually in 1975–1995, with performance varying greatly across industries. Using a similar method, Aswicahyono and Hill (2002) estimate the TFP growth in 28 manufacturing industries over the 1975–1993 period. On average, the TFP growth is 2.3% during that time, while in 1976–1981, TFP grew 1.1%, but between 1981 and 1993, TFP declines by approximately 4.9 % annually.

Vial (2006) applies the Levinsohn and Petrin (2003) production function to estimate TFP growth over the 1988–1995 period. This methodology revisits the previously used growth accounting based elasticities and thereby improves the TFP estimates. The results show that the aggregate TFP growth in Indonesian manufacturing is higher than has previously been estimated.

Wengel and Rodriguez (2006) estimate labour productivity in manufacturing industries, focusing on the dynamic entry-exit of firms and plan size for the 1994–2000 period. The overall change in manufacturing labour productivity reaches 27.2%, and the annual average growth is 3.5%. Similarly, Takii and Ramstetter (2005) analyse labour productivity, focusing on the contributions of multinational corporations (MNCs) for the 1975–2001 period. MNCs generally experiences much higher average labour productivity than local plants. There are also large variations in the MNC presence and in MNC-local productivity differentials across industries and time.

Unlike the above-mentioned studies, several studies use the stochastic production frontier (SPF) approach to estimate firm productive efficiency and productivity growth. The first study is conducted by Pitt and Lee (1981). By implementing several estimation models, these authors measure firm productive efficiency in the weaving industries for the 1972, 1973 and 1975 periods. One of the results indicates that the average efficiency of the weaving industries is 61.8%. The work of Pitt and Lee (1981) is a pioneering study in measuring firm productive efficiency using the stochastic production frontier approach (SPF) in Indonesia.

Hill and Kalirajan (1993) examine the technical efficiency of the garment industry using the 1986 manufacturing census. The analysis suggests that inter-firm variations in efficiency are considerable. Further, by including the spatial perspective, Battese et al. (2001) examine the technical efficiency of firms in the garment and textiles industry across five different regions, involving different technologies. Technical efficiency is approximately 66 % for all regions during the 1990–1995 period, with the lowest being 48.5 % for Jakarta and the highest being 83.7 % for East Java.

Ikhsan (2007) investigates the pattern of total factor productivity (TFP) growth and its decomposition in Indonesian manufacturing industries over the 1988–2000 period using the stochastic frontier production function. The results show that TFP growth was 1.55% between 1988 and 2000. The pattern of technical efficiency changes suggests the existence of a learning-by-doing effect in the adoptions of technology. In a similar approach, Margono and Sharma (2006) estimate TFP growth and its decomposition in selected manufacturing industries from 1993 to 2000. The results reveal that the technical efficiencies of the food, textile, chemical and metal products industries are, on average, 50.79%, 47.89%, 68.65% and 68.91%, respectively.

A recent study is conducted by Suyanto et al. (2009). It analyses the contribution of spillovers from foreign direct investment (FDI) to productivity growth in the chemical, pharmaceutical, garment and electronics industries. The results indicate positive productivity spillovers from FDI A higher level of competition is associated with larger spillovers and domestic firms with R&D benefit from more spillover benefits in comparison to those without R&D.

Using a similar approach, Suyanto et al. (2012) analyse the FDI spillovers and productivity growth at garment and electronics industries. TFP growth is positive with an average 2.33% in garment industry for the 1988–2000 period. In contrast, the TFP growth in electronics industry declines by average -0.70% per annum. Furthermore, Suyanto and Salim (2013) estimate the effect of FDI spillovers on firm technical efficiency in pharmaceutical industry over the period 1990–1995. The results from the stochastic frontier approach show that domestic firms are more efficient than foreign firms. Table 3.5 presents a summary of the studies on productivity growth in Indonesia.

Table 3.5: A Summary of Selected Empirical Studies on Productivity Growth in the Indonesian Manufacturing Industry

No.	Authors	Period of Data	Industry	Core of Study	Key Finding
1.	Aswicahyono et al. (1996)	1976–1991	Manufacturing industry	TFP growth	TFP growth rates are 0.7%, 1.1%, and 2.6% for the periods 1976–1981, 1981–1985, and 1986–1991, respectively.
2.	Timmer (1999)	1975–1995	Manufacturing industry	TFP growth	TFP growth averaged 3% annually in 1975–1995 and performance varied greatly across industries
3.	Aswicahyono and Hill (2002)	1975–1993	28 manufacturing industries	TFP growth	TFP growth is 2.3% during 1973–1993
4.	Vial (2006)	1988–1995	Manufacturing industry	TFP growth	Applying the Levinsohn and Petrin (2003) production function, TFP growth in Indonesian manufacturing was higher than had previously been estimated.
5.	Wengel and Rodriguez (2006)	1994–2000	Manufacturing with dynamic entry-exit of firms	Labour productivity	Average growth of 3.5% annually
6.	Takii and Ramsetter (2005)	1975–2001	Multinational Corporation	Labour productivity	Labour productivity in MNCs tends to be higher than in local plants
7.	Pitt and Lee (1981)	1972, 1973 and 1975	Weaving industries	TFP and technical efficiency	The mean of efficiency level is 61.8 %
8.	Hill and Kalirajan	1986	Manufacturing	Technical efficiency	Inter-firms variations in efficiency

No.	Authors	Period of Data	Industry	Core of Study	Key Finding
	(1993)		industry		
9.	Battese et al. (2001)	1990–1995	Textile and garment industries across six different regions	Technical efficiency	Technical efficiency is approximately 66% for all regions
10.	Ikhsan (2007)	1988–2000	Manufacturing industry	TFP growth and its decomposition	• TFP growth was 1.55% between 1988 and 2000 • Technical efficiency changes suggests the existence of a learning-by-doing effect in technology adoptions
11.	Margono and Sharma (2006)	1993–2000	Selected manufacturing industries	TFP growth and its decomposition	TE are 50.79% (food), 47.89% (textile), 68.65% and 68.91% (chemical)
12.	Suyanto et al. (2009)	1988–2000	Chemical and pharmaceutical industries	TFP growth and its decomposition; FDI spillovers	Positive productivity spillovers from FDI
13.	Suyanto et al. (2012)	1988–2000	Garment and electronics industries	TFP growth and FDI spillovers	Annual TFP growth is 2.33% in garment industry and -0.77% in electronics industry.

Source: Author’s compilation

3.6 Conclusion

Empirical studies confirm that agglomeration economies contribute substantially to stimulating productivity growth. Scholars have used various approaches to perform a large number of studies. Most empirical studies refer to the categories of Glaeser et al. (1992), i.e., the Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity) and Porter's externalities (or competition). Most empirical studies are performed at the regional and industry level; the term "regional" is defined as a formal state region, city, or specific local industrial concentration and the term "industry" refers to the aggregate or sub-sector level.

Various indicators are used as proxies for the variables. Research focusing on analysing economic growth uses employment growth as a proxy or uses other variables such as the number of new firms, wage growth, plant size, the number of employees per firm, the number of plants or the number of employees per area. Some research focuses on analysing agglomeration economies and productivity growth by using common proxy variables, such as output per labour hour, total production factors, value-added growth, efficiency scores or capacity to export to represent firm productivity. When the data for capital stock are available throughout a series of times periods, total factor productivity (TFP) growth can be measured.

An econometric model is the most frequently used method for examining the effect of agglomeration economies on productivity growth. For example, Rosenthal and Strange's (2004) model augments a standard production function. Unlike the earlier models that generally used only single factor of production, this approach accommodates multiple inputs or production factors. The measurement of productivity has also been developed from a single input, such as labour productivity to the total factor productivity (TFP) and its decomposition.

The empirical evidence has resulted in various findings. Most findings correlate with the theory, but some oppose it. The differences in the empirical findings are possibly due to technical factors, especially in relation to the variables of construction, the model specifications, and the data or the economic environment in which the research is conducted. Beaudry and Schiffauerova (2009) identifiy five strategic aspects that should be considered in this research, namely the role of knowledge externalities, the indicators of agglomeration economies, the industrial classifications, geographical considerations, and the performance measures for regions and firms.

From an international perspective, a number of studies on the effect of agglomeration economies upon productivity growth are available. However, there are only a few studies from an Indonesian perspective. Recent studies performed by Kuncoro (2009) and the World Bank (2012) analyse the impact of urbanization and localization on productivity using real value-added per labour as a proxy variable. Moreover, the productivity level is primarily measured using a single input such as labour productivity and almost no empirical studies consider the effect of agglomeration on productivity by applying the concept of total factor productivity (TFP) growth and its decomposition.

Given the paucity of detailed research on the effects of agglomeration economies on productivity growth in Indonesia, this thesis analyses the relationship between agglomeration economies and total factor productivity growth using the appropriate techniques and data. The study will be performed on the aggregate and two-digit manufacturing industries over 33 provinces in Indonesia. The measurement of TFP growth uses the Färe-Primont productivity index as proposed by O'Donnell (2012). A detailed discussion of these issues is presented in the next chapter.

Chapter 4

The Analytical Framework

4.1. Introduction

As described in Chapter 1, the main objective of this thesis is to examine the effects of agglomeration economies on firm-level productive efficiency and productivity growth, including the decomposition of total factor productivity (TFP) growth and identification of its various sources. To achieve these objectives, an appropriate approach is required with respect to the nature of agglomeration economies and firm productivity. This chapter discusses the analytical frameworks to be used in this thesis.

In general, early studies on the effect of agglomeration economies on productivity growth use a simple production function. However, more recent works analyse agglomeration economies within the broader framework of production function or by applying other models such as cost functions, growth models, and the factor price equation (Graham and Kim 2008). Various estimation models that have been applied in the empirical analysis of the effect of agglomeration economies on productivity growth include, for example, an augmented translog production function applied by Rosenthal and Strange (2004) and a generalized translog production function system based on the inverse input demand framework proposed by Kim (1992).

Recently, the translog production function is more frequently applied because it is more flexible and requires only a few restrictions on the data. In addition, scale economies are variable, unlike the Cobb-Douglas production function, which is constrained to a constant returns to scale. The translog function imposes fewer technical assumptions than the other popular functional forms (Feser 2002).

Another interesting issue in recent analyses of the effect of agglomeration economies on productivity growth is the use of the micro-level approach, in which the study is conducted at the firm level rather than at the aggregate industry level. This approach has distinct advantages. Because the nature of agglomeration is actually micro-behaviour, using micro-level data allows us to estimate the effects of firms' external local environment on their productivity level, including a set of firms' attributes

(Andersoon and Lööf 2011). A micro-level framework also permits the estimation of the effect of agglomeration economies at the most fit spatial scale (Feser 2002).

Empirical studies of the effect of agglomeration economies on firm-level productive efficiency using the framework of the stochastic production frontier (SPF) are very limited. As briefly discussed in Chapter 3, the implementation of the SPF framework does not usually relate to investigation of the effects of agglomeration economies. This thesis is one of the first to apply SPF to examine the impact of agglomeration economies on firm-level productive efficiency in the Indonesian case. With this method, following Battese and Coelli (1995), the agglomeration economies variables as determinants of firm-level productive efficiency are estimated simultaneously in the framework of the translog production frontier.

Various approaches can be applied for the measurement of industrial agglomeration, depending on the nature of the research and the availability of the data. Beaudry and Schiffauerova (2009) note that approximately 75 percent of the studies in this field apply location quotient (LQ) to represent the specialization because LQ is a simple method to map the concentration of manufacturing industry. In this method, a particular region is identified as having a relative advantage compared to other regions.

This chapter discusses the analytical tools to be used to estimate the relationship between agglomeration economies and productivity growth. This chapter is organized into seven sections. Following the introduction, Section 4.2 discusses the concept of technical efficiency. Section 4.3 explains the stochastic frontier approach (SFA) for estimating the effect of agglomeration economies on firm-level productive efficiency. Section 4.4 discusses the measurement of agglomeration. Further, Section 4.5 analyses the decomposition of total factor productivity (TFP) growth. Section 4.6 describes the estimation method to examine the effect of agglomeration economies on productivity growth. Finally, Section 4.7 concludes the chapter.

4.2. Technical Efficiency

Farrell (1957) is widely recognized as the pioneer in constructing the operational measurement of technical efficiency. He proposes two basic concepts of firm efficiency, namely, technical efficiency and price efficiency. Later, the term price efficiency becomes more commonly known as allocative efficiency, which refers to the general allocative efficiency resulting from the choice of production factor by firms (Coelli et al. 2005).

After the seminal work of Farrell (1957), there has been rapid progress in the development of the approach, methodology, and technique for measuring firm-specific efficiency and productivity growth. Technical efficiency is defined as the ratio of the observed output to the corresponding frontier output at given technology, conditional on the levels of inputs used by the firm (Battese 1992). The measure of technical efficiency can be derived from the stochastic production frontier. The general equation of the stochastic production frontier can be written as:

$$y_i = f(x_i;\beta)\ exp(-u_i). \quad (4.1)$$

Equation (4.1) shows the deterministic component of the stochastic production function, $y_{it}=f(x_{it},t,\beta)$, together with a stochastic technical efficiency component, u_{it}, allowing for random shocks to output then yields:

$$y_{it} = f(x_{it},t,\beta)\ exp(\varepsilon_{it}) \text{ where } \varepsilon_{it} = (v_{it}-u_{it}). \quad (4.2)$$

Equation (4.2) adds a random error term, and the time variant is accommodated by u_{it}, where the u_{it} terms are replaced by u_i; so that the efficiency component is time-invariant.

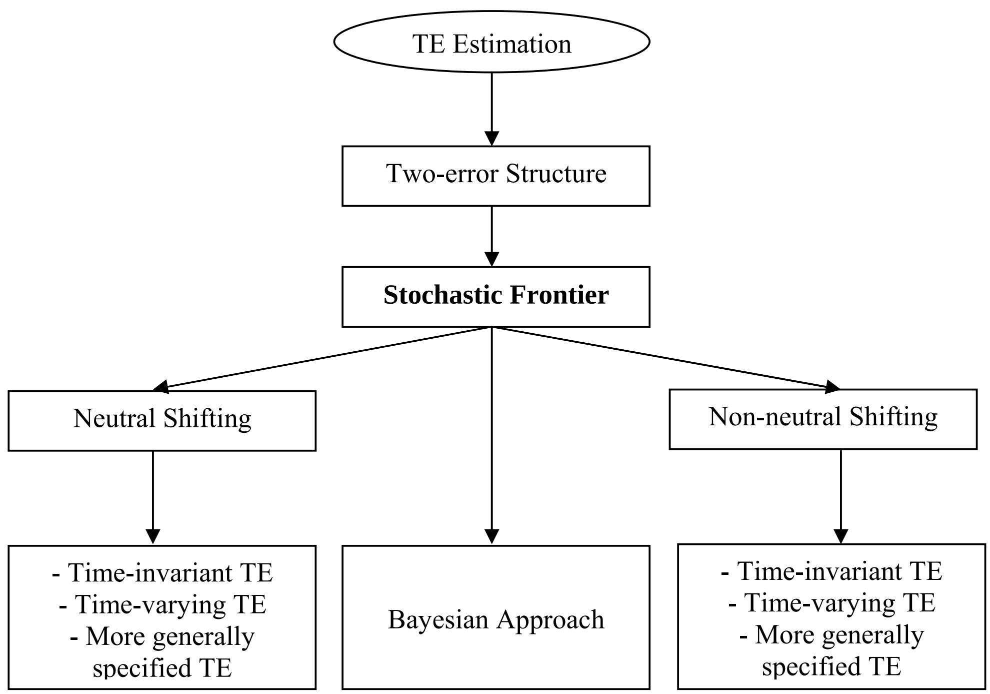
In Equation (4.2), i=1,2,3,…m represents the i^{th} firm, t=1,2,3,…T denotes the t^{th} time period or time trends used as a proxy for technological change, x_{it} is production factors for firm i at time t, or (*1xk* inputs vector), and β is a vector of parameters or (*kx1* vector of parameters) to be estimated. Then, ε_{it} is the stochastic error term that has two independent unobservable components v_{it} and u_{it}. v_{it} is a stochastic variable that represents a random variation in output due to uncontrolled shocks (Pitt and Lee 1981; Coelli 1996). v_{it} is assumed to be independently and identically distributed *(iid)* as N$(0,\sigma_v^2)$, while u_{it} represents technical inefficiency in production and is assumed to be independently distributed with truncation at zero of the N(u_i,σ_u^2) distribution.

The technical efficiency of production for the i^{th} firm in the context of the stochastic production function is defined as the ratio of the observed output to the maximum possible frontier output. Thus, technical efficiency (TE) is expressed as:

$$
\begin{aligned}
TE_{it} &= Y_{it}/Y^*_{it} \\
&= f(x_{it},t,\hat{a})\ exp(v_{it}-u_{it})/\ f(x_{it},t,\hat{a})\ exp(v_{it}) \\
&= exp(-u_{it}) \qquad (4.3)
\end{aligned}
$$

where Y^*_{it} is the maximum possible frontier output that is not observable but can be estimated from given inputs in production (Battese and Coelli 1995).

Figure 4.1: Technical Efficiency Estimation under the Stochastic Frontier



Source: Mahadevan (2004), p.54

Theoretically, several approaches can be applied to estimate technical efficiency under the stochastic production frontier. Figure 4.1 provides a brief summary of technical efficiency measuring methods commonly used in empirical analysis. The more generally specified TE in this figure includes the varying coefficients stochastic frontier (VCSF) as proposed by Kalirajan and Obwona (1994). Many studies note that methods used to estimate technical efficiency are continuously developed to obtain the best estimation results. A more recent estimation approach assumed that firm-specific factors affecting technical efficiency should be incorporated into the model. This model is estimated simultaneously in one stage to obtain parameters of stochastic frontier and technical inefficiency effects. The discussion of this approach is presented in the following section. This method is used to estimate the impact of agglomeration economies on firm-level productive efficiency.

4.3. The Stochastic Production Frontier (SPF)

Following Battese and Coelli (1995), this thesis uses the framework of the stochastic production frontier to estimate the effect of agglomeration economies on firm-level productive efficiency. Considering the previous discussion, this section describes the nature of the stochastic production function and the technical inefficiency function, which are estimated simultaneously in one stage.

4.3.1. The Origin of the Concept of the Stochastic Production Frontier

The implementation of the SPF approach for measuring total firm-level productive efficiency and productivity was initiated by Farell (1957). However, it was not until the late 1970s that this approach was formalized and used for empirical investigation. In addition, scholars agree that two papers published almost simultaneously by two teams, Meeusen and van Broeck (1977) and Aigner, Lovell, and Schmidt (1977), originated the implementation of the stochastic production frontier.

These two papers propose a new approach to the estimation of the production function by modifying the error term into two components. The first component is normally distributed and represents random statistical noise factors such as weather, luck, measurement errors, and other unpredictable aspects beyond a firm's control. The second error term captures the technical inefficiency of the firm. The functional form proposed by the two papers can be expressed as:

$$Y_i = f(\boldsymbol{X}_i; \alpha_0; \boldsymbol{\beta}).exp(v_i - u_i) \tag{4.4}$$

where Y_i is the scalar output of firm i $(i=1,2,...,N)$,

$f(\boldsymbol{X}_i; \alpha_0; \boldsymbol{\beta}).exp(v_i)$ is the stochastic production frontier,

$\boldsymbol{X}_i$ is a $(1xk)$ vector of inputs used by firm i,

$\boldsymbol{\beta}$ is a *(kx1)* vector of slope parameters,

$exp(v_i-u_i)$ is the combined error term,

v_i is the two-sided random statistical noise of firm *i*, with *iid* $N(0,\sigma_v^2)$, and

u_i is the one-side error component representing technical inefficiency.

In the linear model, Equation (4.4) can be written as:

$$y_i=\alpha_0+x_i\beta+v_i-u_i \tag{4.5}$$

or

$$y_i=\alpha_0+[x_{1i} \quad x_{2i} \quad x_{3i} \dots x_{ki}]\begin{bmatrix}\beta_1\\ \beta_2\\ \beta_3\\ .\\ .\\ .\\ \beta_k\end{bmatrix}+v_i-u_i. \tag{4.6}$$

As mentioned previously, y_i stands for the scalar of the logarithm of output for firm *i* $(i=1,2,...N)$, and x_i is a vector of the logarithm of inputs used by firm *i* with dimension *(1xk)*.

Aigner et al. (1977) explain that the basic idea of the stochastic production frontier is to overcome the previous model, which does not utilize an adequate characterization of the disturbance term. The conventional production function, which expresses that the maximum output of a firm can be achieved by given input bundles with fixed technology, assumes that firms work at the maximum efficiency level. The conventional production function can be expressed as:

$$y_i=f(x_i;\beta) \tag{4.7}$$

where y_i is the maximum output obtainable from x_i, a vector of inputs, and β is an unknown parameter vector to be estimated.

Aigner et al. (1977) introduce a new specification by dividing the error terms into two components, as shown in Equation (4.4). The model in Equation (4.4) is called the stochastic production frontier because the output values are bounded from above by the stochastic variable $exp(x_i'\beta+v_i)$ (Coelli et al. 2005). This stochastic frontier model is consistent with economic theory. Thus, the stochastic production frontier specification can be used not only to estimate the parameter of production technology β but also to measure the technical efficiency.

In Equation (4.4), the error component v_i represents the symmetric disturbance, which is assumed to be independently and identically distributed *(iid)* as $N(0,\sigma_v^2)$. The error component u_i is assumed to be distributed independently of v_i and to satisfy $u_i \leq 0$. In the distributional assumptions, Aigner et al. (1977) consider the half normal and the exponential distribution to u, while Meeusen and Broek (1977) assign the exponential distribution to u; Battese and Corra (1977) implement the half normal distribution to u.

Regarding the estimation procedure, the pioneering papers of Aigner et al. (1977) and Meeusen and van den Broek (1977) propose the maximum-likelihood (ML) method given their distribution assumptions of the two error terms. In this regard, Khumbakar and Lovell (2000) state that either distribution assumption for u implies that the composed error (v_i-u_i) is negatively skewed, and statistical efficiency requires that the model is estimated by maximum likelihood. Based on this assumption, the early stochastic production frontier model is applicable to cross-sectional data.

After the two pioneering papers, researchers have continued to develop the stochastic production frontier by implementing more flexible distribution forms and applying other models such as panel data. Regarding distribution forms, Greene (1980) applies normal and gamma distributions by introducing additional parameters to be estimated. Similarly, Stevenson (1980) suggests normal and truncated-normal distributions. Nonetheless, the two original single-parameter distributions remain the distributions of choice in the vast majority of empirical work (Kumbhakar and Lovell 2000).

The possibility of choosing various distribution forms raises the question whether the distributional assumption substantially affects the measurement of technical efficiency. Khumbakar and Lovell (2000) state that it is unclear whether a ranking of producers by their individual efficiency scores or by the composition of the top and bottom efficiency score deciles is sensitive to distributional assumptions. Coelli et al. (2005) note that the final consideration when choosing between models is that different distributional assumptions can result in different predictions of technical efficiency.

The estimation result made by Greene (1990) is an example in which the mean of the technical efficiency scores tends to be sensitive to the distributional assumption. Ritter and Simar (1997), as emphasized by Coelli et al. (2005), argue for a relatively simple distribution, such as half normal or exponential, rather than a more flexible distribution, such as truncated normal or gamma. This argument is supported by empirical evidence in Horrace (2005) and Khumbakar and Lovell (2000). Their empirical findings endorse the idea that the choice among various available distributional assumptions is largely immaterial.

4.3.2. Stochastic Production Frontier in the Panel Data Model

The discussion of probability distribution assumptions mentioned in the previous sub-section relates to the cross-sectional model. Recently, the panel data structure has been extensively used for the stochastic production function estimation because it allows more relaxed assumptions. Pitt and Lee (1981) cite four reasons why panel data are preferred in the analysis. First, panel data allows observations over a number of years to test structural changes in the production function. Second, it is impossible to estimate the efficiency of individual firms from a single cross-sectional data set. Third, the panel data model permits comparison of traditional analysis with the covariance approach. Fourth, the panel data model allows investigation into whether the inefficiency of firms is time-variant or time-invariant.

Lee (2006) states that, by making repeated observations over time for a given company, the panel data structure can serve as a substitute for the distributional assumptions. Panel data allow more accurate statistical properties. Moreover, Schmidt and Sickles (1984) note that panel data provide a more accurate measure of technical efficiency (u_i) when they are separated from the stochastic noise of a firm's level (v_i). Further, no specific distributional specification is necessary for the consistent estimation of parameters and panel data facilitate the relaxing assumption that inefficiency and factor input levels are independent.

Based on Equation (4.4), the stochastic production function in the panel data structure can be written as:

$$Y_{it}=f(X_{it};\alpha,\beta).exp(v_{it}-u_i) \quad (4.8)$$

The difference between Equation (4.4) and Equation (4.8) is the subscript *t,* which shows the time dimension. The additional *t* reflects the fact that the data are in a panel structure that consists of a cross-sectional dimension of $i = (1, 2, 3,..., N)$ and a time dimension of $t = (1, 2, 3,..., T)$. In a linear model, Equation (4.8) can be written as:

$$\begin{aligned} y_{it} &= \alpha_0+x_{it}\beta+v_{it}-u_i \\ &= \alpha_i+x_{it}\beta+v_{it} \qquad \text{where } \alpha_i=\alpha_0-u_i \end{aligned} \quad (4.9)$$

or

$$y_{it}=\alpha_i+[x_{1it} \quad x_{2it} \quad x_{3it} \ldots x_{kit}]\begin{bmatrix}\beta_1\\ \beta_2\\ \beta_3\\ .\\ .\\ .\\ \beta_k\end{bmatrix}+v_{it}. \quad (4.10)$$

In Equation (4.9), y_{it} is the scalar of the logarithm output of the firm i $(i=1,2,...,N)$ at time t $(t=1,2,...T)$, x_{it} is a (lxk) vector of the logarithm of production inputs used by firm i at time t, β is a (kxl) vector of unknown parameters, and $\alpha_i=\alpha_0-u_i$ is the intercept for firm i that is invariant at all times t.

The panel data SPF expressed in Equation (4.8) can be recognized as the early model of SPF in panel structure by assuming time-invariant technical efficiency. Shortly after publication of the two original papers on SPF by Aigner et al. (1977) and Meeusen and van Broek (1977), some studies that apply panel data SPF were published. Pitt and Lee (1981) are the first researchers who applied SPF on panel data, followed by Schmidt and Sickles (1984). In their study, Pitt and Lee (1981) extend the basic cross-sectional model into panel data by applying several estimation models under maximum likelihood procedure. On the other hand, Schmidt and Sickles (1984) apply fixed effects and random effects of panel data on SPF.

4.3.3. Time-Varying Technical Efficiency

The assumption of time-invariant technical efficiency in Equation (4.8) is restrictive, especially if the firms operate in a competitive environment. The notion that technological inefficiency remains constant over many periods is hard to accept (Kumbhakar and Lovell 2000). Technical efficiency is expected to change over time as firms play in the market and learn from their previous experiences in the production process. This consideration leads to a desirable relaxation of the assumptions. Consequently, scholars introduce a new approach by replacing time-invariant technical efficiency with time-variant technical efficiency for panel data.

Time-variant technical efficiency is proposed by, for example, Khumbakar (1990), Cornwell et al. (1990), and Battese and Coelli (1992). The initial two studies are perhaps the first to propose a stochastic production frontier model with time-variant technical efficiency. In general, the SPF model with time-varying technical efficiency can be written as:

$$\begin{aligned} lny_{it} &= \alpha_{0t} + \textstyle\sum_n \beta_n lnx_{nit} + v_{it} - u_{it} \\ &= \alpha_{it} + \textstyle\sum_n \beta_n lnx_{nit} + v_{it} \end{aligned} \quad (4.11)$$

where α_{0t} is the production frontier intercept common to all producers in period t, and $\alpha_{it}=\alpha_{0t}-u_{it}$ is the intercept for producer i $(i = 1, 2, ..., I)$ in period t $(t = 1, 2, ..., T)$. The difference in Equation (4.11) from Equation (4.8) is that an additional subscript t in u reflects the time-varying technical efficiency.

Khumbakar (1990) formulates the technical efficiency effect as a product of an exponential of time with two parameters, γ and δ, as well as a time-invariant non-negative random variable, u_i. The model can be written as:

$u_{it}=g(t)u_i$; and

$$g(t)=[1+exp(\gamma t+\delta t^2)]^{-1} \quad (4.12)$$

Equation (4.12) allows the level of technical inefficiency to be variable, and the temporal pattern is the same for all firms because it is determined by form $g(t)$. The estimation of this model uses the maximum likelihood (ML) approach. Empirically, Khumbakar's (1990) model is rarely implemented (Coelli et al. 2005).

Battese and Coelli (1992) propose another alternative to Khumbakar's (1990) model. The difference lies in the function of time. The time-varying technical efficiency suggested by Battese and Coelli (1992) is written as:

$u_{it}=\{exp[-\eta(t-T)]\}u_i$; and (4.13)

η is an unknown parameter to be estimated.

In Equation (4.13), the technical inefficiency effect for the i^{th} firm is not the same for different periods of observation. In the last period, the technical inefficiency is represented by u_i, while in the earlier periods in the panel the technical inefficiency effects are the product of u_i and the value of the exponential $exp[-\eta(t-T)]$. The value depends on η and the number of periods in the panel before the last period, $(T-t)$.

Mahadevan (2004) notes that the disadvantage of the models in both (4.12) and (4.13) is their rigid parameterization. In particular, the technical efficiency in (4.12) must either increase at a decreasing rate (η>0), decrease at an increasing rate (η<0), or simply remain constant (η=0). Therefore, the model does not capture the condition in which particular firms may be relatively inefficient in the beginning but become more efficient in subsequent periods.

Cornwell et al. (1990) specify a model of technical inefficiency that relaxes the rigid parameterization by assuming that the intercept of the parameters for different firms at different time periods is a quadratic function of time *(t)* with the coefficients varying over firms according to multivariate distribution. The model can be expressed as:

$\alpha_{0it}=\delta_{i0}+\delta_{i1}t+\delta_{i2}t^2$; (4.14)

where δ_{ij} are parameters to be estimated. The advantage of the model in Equation (4.14) compared with Kumbhakar's (1990) and Battese and Coelli's (1992) model is that it uses generalized least square (GLS). Hence, there is no need to specify any special density function of u_{it}. This model allows the technical inefficiency change to vary over time, but does not assume the same rate for all firms. The specification is also useful for relatively short periods.

Lee and Schmidt (1993) specify another time-varying technical efficiency by introducing time dummy variables:

$u_{it}=\theta_t u_i$ (4.15)

where $\theta_t=[\theta_1,\theta_2,\ldots,\theta_T]$ is a set of time dummy variables. Because θ_1 is normalized to $\theta_1=1$, the number of intercept parameters reduces to *(T-1)*. Lee and Schimdt's (1993) model has the advantage of flexibility in the pattern of technical efficiency over time compared with the model of Cornwell et al. (1990). The disadvantage is that this model requires a general time pattern of variation in technical efficiency for all producers. This model is useful for panel data with a short time series.

There is another model of time varying stochastic frontier as the extension of the former frontier models. The model is known as the varying coefficients stochastic frontier (VCSF) or input-specific technical efficiency model as proposed by Kalirajan and Obwona (1994). They argue that the parallel-shifting frontier is not logical, where it essentially remains constant with the exception of the intercept term. The main idea of this model is that observation-specific production behaviour should be included, which results in different factor response coefficients across observations. Technical efficiency depends on the method of applications of inputs without consider the levels of the inputs use. As consequence, the intercept and coefficient in the frontier model will vary from firm to firm. This is the basis of concept of non-neutrality in the analysis. Even though the VCSF model is an extension of the basic production frontier model, this model is more complicated than the conventional production frontier. In application, the model cannot be estimated when the number of parameters exceeds the number of observations.

4.3.4. Stochastic Production Frontier Model with Variables Explaining Inefficiency

In the stochastic production frontier, u_{it} represents the technical efficiency of firms, while v_{it} represents the random error associated with factors that are not under the control of the firm, such as measurement errors in production, weather, industrial action. Among the determinants of u_{it} there can be a set of independent variables, such as firm size, age of firm, ownership and regional location, that influence inefficiency. In the general model of the stochastic production function, as discussed previously, these variables are not simultaneously integrated into the model for the technical inefficiency effect in the stochastic production function.

Since the first two papers on SPF published in 1977, the common method applied to estimate the stochastic production function is a two-stage approach. The first stage covers the specification and estimation of the stochastic production function and the prediction of the technical inefficiency effects, under the assumption that inefficiency effects are identically distributed. The second stage covers the specification of a regression model for the predicted technical inefficiency effects (Battese and Coelli 1995). This approach means that the coefficients of variables that affect technical inefficiency are not estimated simultaneously in one stage. There is a fundamental weakness of the two-stage approach, because the estimation procedure in the second stage violates the assumption of identically distributed inefficiency effects in the stochastic frontier (Coelli et al. 2005).

Considering the weakness of the two-stage approach, scholars have proposed another model for technical inefficiency effects in the stochastic production function for panel data that accommodates random factors into the model. The general specification of the model is written as:

$$y_{it}=\alpha_{0t}+x_{it}\beta+v_{it}-u_{it} \tag{4.16}$$

$$u_{it}=z_{it}\gamma+\varepsilon_{it} \tag{4.17}$$

where z is a $(1xm)$ vector of independent variables affecting the technical inefficiency of production, γ is a $(mx1)$ vector of parameters of the technical inefficiency function, and ε is a random variable. The technical inefficiency function can also be expressed as:

$$u_{it}=\gamma_0+\gamma_1 z_{1it}+\gamma_2 z_{2it}+\gamma_3 z_{3it}+\ldots+\gamma_n z_{nit}+\varepsilon_{it} \tag{4.18}$$

where z_{1it}, z_{2it}, z_{3it}, . . ., z_{nit} are n explanatory variables suspected of being factors contributing to inefficiency, γ_1, γ_2, γ_3, . . ., γ_n are parameters to be estimated, and ε_{it} is an error term.

Among the scholars pioneering this approach are Kumbhakar et al. (1991), Reifschneider and Stevenson (1991), Huang and Liu (1994), and Battese and Coelli (1995). The first three papers use the cross-sectional data in the analysis, while the last paper uses panel data. The parameters of the stochastic frontier and the inefficiency model in Equations (4.16) and (4.17) are estimated simultaneously, given the appropriate distributional assumptions for the data on the sample firms.

This estimation approach is able to overcome the weaknesses of the two-stage estimation method.

To obtain a comprehensive illustration of the model for the technical inefficiency effect in a stochastic frontier production function for panel data, the following will discuss Battese and Coelli's (1995) model, which has recently been widely applied in the relevant research analysing efficiency and productivity. The detailed model is written as follows:

$$y_{it}=\alpha_{0t}+x_{it}\beta+v_{it}-u_{it} \quad (4.19)$$

$$u_{it}=z_{it}\delta+w_{it} \quad (4.20)$$

where y_{it} is the production or output at the t^{th} sample $(t=1, 2, \ldots, T)$ for the i^{th} firm $(i = 1, 2, \ldots, N)$, x_{it} denotes a $(1xk)$ vector of input production used by firm i at time t, β is a $(kx1)$ vector of unknown parameters to be estimated, v_{it} is a random error, u_{it} is the technical inefficiency effects, z_{it} denotes a $(1xm)$ vector of explanatory variables that affect technical inefficiency for firm i at time t, δ is a $(mx1)$ vector of unknown parameters of the inefficiency effect to be estimated, and w is a random error. The assumptions for the above model are:

$$v_{it}\sim N(0,\sigma_v^2), \quad (4.20a)$$

v_{it} is assumed to be IID $N(0,\sigma_v^2)$ random errors, ID of the u_{it};

$$u_{it}\sim N^+(z_{it}\delta,\sigma_u^2), \quad (4.20b)$$

u_{it} is assumed to be ID, such that u_{it} is obtained by truncation of normal distribution with mean $z_{it}\delta$ and variance, σ_u^2;

$$E(v_{it}u_{it})=0, \quad (4.20c)$$

v_{it} and u_{it} are assumed to be independently distributed for all $t = 1, 2, \ldots, T$, and $i = 1, 2, \ldots, N$;

$$E(x_{it}u_{it})=0, \quad (4.20d)$$

no correlation between x_{it} and u_{it};

$$w_{it}\sim N^+(0,\sigma_u^2), \quad (4.20e)$$

w_{it} is a random variable, the truncation of the normal distribution with 0 mean and variance, σ_u^2, and the point truncation is $-z_{it}\delta$.

The assumption in Equation (4.20e) is in accordance with the assumption in Equation (4.20b), where u_{it} is a non-negative truncation of $N(z_{it}\delta)$. The estimation method proposed for the model of Equations (4.19) and (4.20) is the maximum likelihood for simultaneous estimation of the parameters of the stochastic frontier as well as the model for the technical inefficiency effects. In Battese and Coelli (1995), the maximum-likelihood estimates of the parameters of the model are obtained in terms of the parameterization, $\sigma_s^2=\sigma_v^2+\sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{(\sigma_u^2+\sigma_v^2)}$ or $\frac{\sigma_u^2}{\sigma_s^2}$.

Following Battese and Coelli's (1995) model, as expressed in Equations (4.19) and (4.20), this study includes agglomeration economies variables in the technical inefficiency equation. Agglomeration economies contribute to the efficiency of production. Other exogenous variables such as a firm's age, size, etc. that are expected to affect productive efficiency are also included in the model. Thus, the non-random factors that influence technical inefficiency are divided into two categories, namely, agglomeration economies variables and other exogenous variables. The technical inefficiency in Equation (4.20) can then be written as follows:

$$u_{it}=\boldsymbol{AGG}_{it}\rho+\boldsymbol{z}_{it}\delta+\omega_{it} \qquad (4.21)$$

where $\boldsymbol{AGG}$ is a *(1xm)* vector of agglomeration economies variables of firm *i* at time *t*, ρ is a *(mx1)* vector of parameters, $\boldsymbol{z}$ is a *(1xn)* vector of other random factors of firm *i* at time *t*, and δ is a vector of coefficients for other random factors. Then Equation (4.21) can be written in the complete model as follows:

$$u_{it}=\delta_0+LQ_{it}+DIV_{it}+COM_{it}+AGE_{it}+SIZE_{it}+CR4_{it}+DURB_{it}+DLOC_{it}+\omega_{it}. \qquad (4.22)$$

As discussed in Chapter 3, agglomeration economies variables in this thesis consist of MAR externalities or specialization (LQ), Jacobs' externalities or diversity (DIV), and Porter's externalities or competition (COM). Meanwhile, the other non-random factors of firm *i* include firm age (AGE), size (SIZE), market/industrial concentration (CR4), and two dummy variables representing urban region (DURB) and industrial complex (DLOC). Agglomeration of economic activities is the crucial condition for the local transmission process of spillovers. Agglomeration can boost a firm's productive efficiency and productivity because the spatial proximity between firms allows increasing knowledge and technological spillovers. The measurement of agglomeration economies variables is discussed in the following section, while the detailed description of other variables is presented in Chapter 5, together with the empirical analysis.

4.4. The Measurement of Agglomeration

Direct measurement of agglomeration economies has been broadly considered by scholars, but in some particular circumstances it is problematic (McCann 2008). One of the problems is the use of geographic concentration indices to describe the agglomeration of economic activities (Arbia 2001), because those indices do not always clearly represent the phenomenon of spatial concentration. Regardless of the critics and the technical debate on this issue, various measures have been developed to identify agglomeration economies. The measures can be expressed in terms of aggregation across regions or industries, and they are generally computed relative to the broader spatial aggregation by ratios or differences. The measurement of agglomeration economies can be represented by concentration of employment, number of firms, or output. The agglomeration itself may be viewed at the level of specific industry or between industries. Adopting from the study of Nakamura and Paul (2009), the measurement of agglomeration in several categories is presented in the following sub-sections.

4.4.1. Measurement of Industrial Localization: Employment Based

This method measures industrial localization based on the spatial distribution of industry i in terms of employment. It reflects the geographic concentration of industry i (employment) across regions. Consider that there are J regional units and I industries in a country, with the number of employees of industry i in region j denoted by x_{ij}. The spatial distribution of industry i can be formulated as follows:

$$s_{ij}^{C}=\frac{x_{ij}}{\sum_{j=1}^{n}x_{ij}}=\frac{x_{ij}}{x_{i*}}\ ,\ i=1,\dots,I;j=1,\dots,J \qquad (4.23)$$

where s_{ij}^{C} reflects the employment share of industry i, region j, in total (national) industry i employment, or the concentration of industry i in region j relative to all regions. Based on Equation (4.23), the spatial distribution of employment by region for all industries can be measured by aggregating s_{ij}^{C} across all industries, as follows:

$$s_{*j}=\frac{\sum_{i=1}^{I}x_{ij}}{\sum_{i=1}^{I}\sum_{j=1}^{J}x_{ij}}=\frac{x_{*j}}{x_{**}}. \qquad (4.24)$$

Equation (4.24) shows the relative size of economic activity with regard to the share of each region's total employment. Based on Equations (4.23) and (4.24), the location quotient (LQ) can be computed as follows:

$$LQ_{ij}^{C}=\frac{s_{ij}^{C}}{s_{*j}} \text{ or } \frac{x_{ij}/x_{i*}}{x_{*j}/x_{**}}, j=1,\ldots,J \qquad (4.25)$$

LQ reflects the share of industry *i's* activity in region *j* relative to the share of total activity in region *j*, represented in terms of employment. LQ also represents the concentration of industry *i* in region *j* relative to the concentration of aggregate industries in region *j*, compared to the national level. Furthermore, the degree of industry localization in a specific region can be computed by taking the average of LQ over all regions specified as:

$$LOC_{i}^{C}=\frac{1}{J}\sum_{j=1}^{J}\frac{s_{ij}^{C}}{s_{*i}} \qquad (4.26)$$

LOC is often called the industry localization rate. In addition, from the employment share in Equation (4.23), the Hirchman-Herfindahl Index (HHI) can also be computed as another measure of geographic concentration. The formula can be written as:

$$H_{i}^{C}=\sum_{j=1}^{J}(s_{ij}^{C})^{2} \qquad (4.27)$$

If the HHI score is equal to one, the industry is fully concentrated in one region; conversely, if HHI is close to zero, the industry is evenly distributed over a large number of regions.

Another alternative measure of geographic concentration is the "dissimilarity measure" proposed by Audretsch and Feldman (1996). This index is calculated based on the deviation of Equations (4.23) and (4.24), using the absolute value. The formula is written as:

$$G_{i}^{C}=\frac{1}{J}\sum_{j=1}^{J}\left|s_{ij}^{C}-s_{*j}\right|. \qquad (4.28)$$

In Equation (4.28), G expresses the degree of spatial concentration of industry *i*. The spatial distribution of industry is similar to all industries if the value of G is near zero.

Still another way to measure the geographic concentration of industry is by using the Gini location coefficient formulated by Aiginger et al. (1999). This coefficient is calculated based on the concept of the Gini Index, which is usually used to measure income inequality. The Gini location coefficient measures the percentage distribution of industry *i's* employment across regions, which coincides with the percentage distribution of national employment across regions (Nakamura and Paul 2009). The formula is also derived from Equations (4.23) and (4.24) as follows:

$$GINI_i^C = \frac{0.5 - \frac{1}{2J}\sum_{j=1}^{J}\left(s_{ij-1}^C - s_{ij}^C\right)}{0.5\left(1 - \frac{1}{J}\right)}. \qquad (4.29)$$

The value of the GINI Index is between zero and one, where zero means that industries are distributed over regions equally to the distribution of total employment.

4.4.2. Measurement of Regional Specialization: Employment Based

Unlike industrial localization, regional specialization is defined as the share of industry *i's* employment relative to total industry employment in a specific region *j* in contrast with the share of region *j's* employment relative to total (national) employment in industry *i*, as noted in Equation (4.23). As explained by Nakamura and Paul (2009), the level of regional specialization in region *j* with respect to industry *i* is formulated as:

$$s_{ij}^S = \frac{x_{ij}}{\sum_{i=1}^{I} x_{ij}} = \frac{x_{ij}}{x_{*j}},\ i=1,\dots,I; j=1,\dots,J \qquad (4.30)$$

where the denominator shows the aggregation over industries rather than over regions, as for industrial localization. In addition, the industrial composition at the national level can be calculated by:

$$s_{i*} = \frac{\sum_{j=1}^{J} x_{ij}}{\sum_{i=1}^{I}\sum_{j=1}^{J} x_{ij}} = \frac{x_{i*}}{x_{**}}. \qquad (4.31)$$

Similar to the industrial localization previously discussed, regional specialization can also be measured by using the Hirschman-Herfindahl Index (HHI) and location quotient (LQ) methods. Meanwhile, the dissimilarity index of regional specialization can be calculated by using the G-measure, as proposed by Audretsch and Feldman (1996). From Equations (4.30) and (4.31), the regional specialization index relative to national industrial composition can be written as:

$$LQ_{ij}^{S}=\frac{s_{ij}^{s}}{s_{i*}}=\frac{x_{ij}/x_{*j}}{x_{i*}/x_{**}},\ i=1,\ldots,I. \tag{4.32}$$

LQ_{ij}^{S} represents the specialization of industry i in region j relative to the specialization of industry i in aggregated regions. The average of the regional specialization index across industries can be calculated by taking the average value of LQ_{ij}^{S}:

$$LOC_{j}^{s}=\frac{1}{I}\sum_{i=1}^{I}\frac{s_{ij}^{s}}{s_{i*}}, \tag{4.33}$$

If the value of LOC_{j}^{s} is greater than zero, it indicates a high relative level of specialization for region j.

Another measure of regional specialization is offered by Krugman (1991a). Unlike the previous calculation, which stresses the comparison between a particular region and a national level, Krugman's formulation refers to a bilateral comparison between two regions. The two regions are identical in industrial composition if the value is zero (Nakamura and Paul 2009). Krugman's index of regional specialization is expressed as follows:

$$K_{jk}^{s}=\sum_{i=1}^{I}\left|s_{ij}^{s}-s_{ik}^{s}\right|, \tag{4.34}$$

Empirically, this measure has been adopted and implemented by many researchers to compare the specialization between regions or nations. Meanwhile, as in the case of localization, regional specialization can also be computed using the GINI coefficient. This index shows the inequality of the distribution of industrial composition in a particular region compared with the national distribution level.

4.4.3. The Ellison and Glaeser Index

A more complex measurement of geographical concentration is proposed by Ellison and Glaeser (1992). They develop an index to measure the agglomeration level by incorporating plant size and industrial distribution to capture the implied agglomeration economies or to overcome the random distribution of firms across spatial units (Overman and Puga 2008). To address the dependency between industrial distribution and geographic concentration, Ellison and Glaeser (1992) develop a probabilistic location model based on "throwing darts" at firms in a country map. If natural advantages and spillovers among firms do not exist, the probability of a firm locating to a particular region depends only on the geographical size (Nakamura and Paul 2009). The Ellison and Glaeser (EG) Index is written as:

$$\gamma_i^{(EG)} = \frac{\sum_{j=1}^{J} (s_{ij}^{C} - s_{*j})^2 - \left(1 - \sum_{j=1}^{J} (s_{*j})^2\right) \sum_{k=1}^{K} (z_{k\varepsilon i})^2}{\left(1 - \sum_{j=1}^{J} (s_{*j})^2\right)\left(1 - \sum_{k=i}^{K} (z_{k\varepsilon i})^2\right)} \tag{4.35}$$

where $\sum_{k=1}^{K} (z_{k\varepsilon i})^2$ represents the spatial Hirschman-Herfindahl Index (HHI), and s_{ij}^{C} and s_{*j} denote the share of employment in industry i in region j and the total share of employment in industry i in region j, respectively. $\gamma_i^{(EG)}$ represents the combined measures of agglomeration, specifically, the natural advantages and spillovers among firms. A positive value for the EG Index indicates that the level of spatial concentration is greater than the expected value. Furthermore, the EG Index has been modified by Maurel and Sedillot (1999). They emphasize the spillovers generated from the proximity of identical-industry firms.

Ellison and Glaeser (1992) also propose another measurement, known as the co-agglomeration index, to capture inter-industry agglomeration. Co-agglomeration exists if externalities stimulate different industries to be more closely located and vertically integrated so that they have interdependencies in intermediate input transactions. The co-agglomeration feature can be investigated between industrial sectors in the lower level of industrial classification, for example, in a five-digit level ISIC (international standard industrial classification) that is classified in the same three-digit ISIC.

4.4.4. The Measurement of Regional Diversity

In addition to specialization, another important measure related to agglomeration is regional diversity, which refers to the variety of economic activities in a certain region. Agglomeration of economic activities can be driven by urbanization factors, such as consumption, the labour market, and industrial diversity. These factors contribute to accelerating economic activities through different mechanisms.

Consumption diversity increases urban economic activities by offering demand for goods and services. The diversity of the labour market creates demand for different jobs and skills, generally known as "labour market pooling". In addition, industrial diversity affects economic activities through exploration of its-own and inter-industry externalities (Nakamura and Paul 2009).

Several index measurements can be applied to represent regional diversity. Duranton and Puga (2000), for example, apply the inverse of the Hirschman-Herfindahl Index (HHI) of regional specialization to measure the level of diversity. This approach is the most popular in the empirical research. The formula can be written as:

$$DIV_j^A = 1/\sum_{i=1}^{I}\left(s_{ij}^S\right)^2. \tag{4.36}$$

When the value of DIV_j^A is equal to I (the number of industries in the industrial classification), industrial employment in region j is distributed among all industries at the maximum level of diversification.

Henderson et al. (1995) offer a different diversity index to identify sectoral diversity by considering a particular industry without involving its own-industry effects. The index can be written as:

$$DIV_{ij}^B = \sum_{i'=1,i'\neq i}^{I}\left(s_{i'j}^S\right)^2. \tag{4.37}$$

Combes (2000) generates an extension of Henderson's et al. (1995) definition by applying an inverse of the Herfindahl Index of sectoral concentration, which refers to the share of all industries without excluding the own industry.

$$DIV_{ij}^C = \frac{1/\sum_{i'=1,i'\neq i}^{I}\left(x_{i'j}/x_{-i,j}\right)^2}{1/\sum_{i'=1,i'\neq i}^{I}\left(x_{i'*}/x_{-i*}\right)^2} \tag{4.38}$$

Equation (4.38) implies that the numerator is maximized when all industries except the own industry have the same size in region j. Similar to HHI, the modified Gibbs-Martin Index (GMI) is also used to describe the labour force concentration in a particular region. As noted by Nakamura and Paul (2009), this index is developed by Gibbs and Martin (1962). If the GMI is zero, the labour market is fully concentrated in one industry. Conversely, if the value is one, the labour market is distributed equally among all the industries. The formula for GMI is written as:

$$GMI_j = 1 - \sum_{i=1}^{I} (x_{ij})^2 / \left(\sum_{i=1}^{I} x_{ij}\right)^2 \qquad (4.39)$$

Another diversity measurement based on the Herfindahl Index is the entropy index (EI). The interpretation of this index is similar to that of the GMI Index. This index is written as:

$$EI_j = - \sum_{i=1}^{I} \frac{x_{ij}}{x_{*j}} log \frac{x_{ij}}{x_{i*}} \qquad (4.40)$$

Most of the empirical studies view diversity as the opposite of specialization. In this case, Nakamura and Paul (2009) note that diversity does not represent the flip side of specialization. As considered by Malliza and Ke (1993), diversity is not simply the total absence of specialization, and it fully represents the uniform distribution of economic activities in an urban area, but diversity also reflects the presence of multiple specializations (specialized diversity).

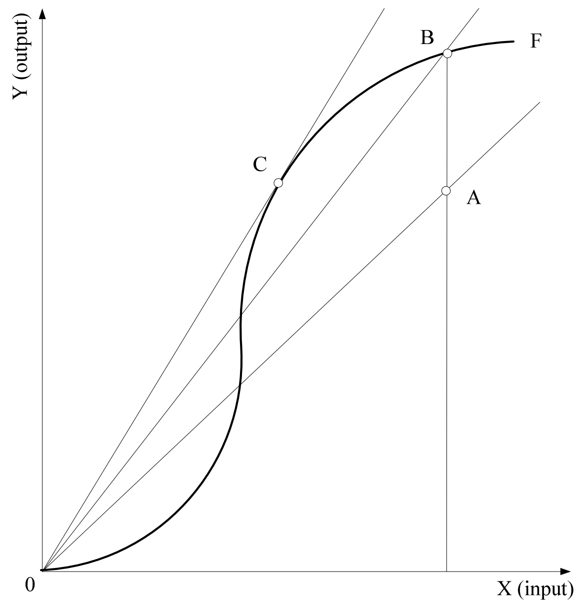
4.5. The Decomposition of Total Factor Productivity Growth

In general, productivity is defined as the relationship between inputs and outputs in the framework of the production function. Productivity is generally measured in the form of a single input or multiple inputs, also known as a partial measure or a total factor productivity measure. This section discusses the method for measuring TFP growth used in this thesis.

4.5.1. Basic Concept of Productivity and Efficiency

As widely described in the literature on productivity analysis by, for example, Coelli et al. (2005) and Khumbakar and Lovell (2000), the basic concept of productivity and efficiency can be derived from a simple production function. Figure 4.2 illustrates the nature of productivity and efficiency.

Figure 4.2: Productivity and Efficiency Framework



Source: Mahadevan (2004), p.7

Suppose a firm uses a single input (X) to produce a single output (Y); the curve 0F represents the "production frontier". The production frontier is defined as the maximum output attainable from a combined set of inputs used in production. The frontier also reflects the current level of technology applied in the industry and shows the efficient level of input-output combination in the production function.

In Figure 4.2, firms operate their production either at the frontier line if they achieve the maximum efficiency level or below the frontier line if they are not technically efficient. At point B, firms operate at the maximum efficiency level, while at point A firms are inefficient because technically they could increase their production to point B with the same quantity of inputs. The distance AB represents the technical inefficiency. Based on the illustration in Figure 4.2, technical efficiency is defined as the improvement of the production process toward the frontier, where the improvement is driven by the internal conditions of the firm, specifically the efficient use of production inputs due to the accumulation of knowledge, new technology, and improved managerial ability (Mahadevan 2004).

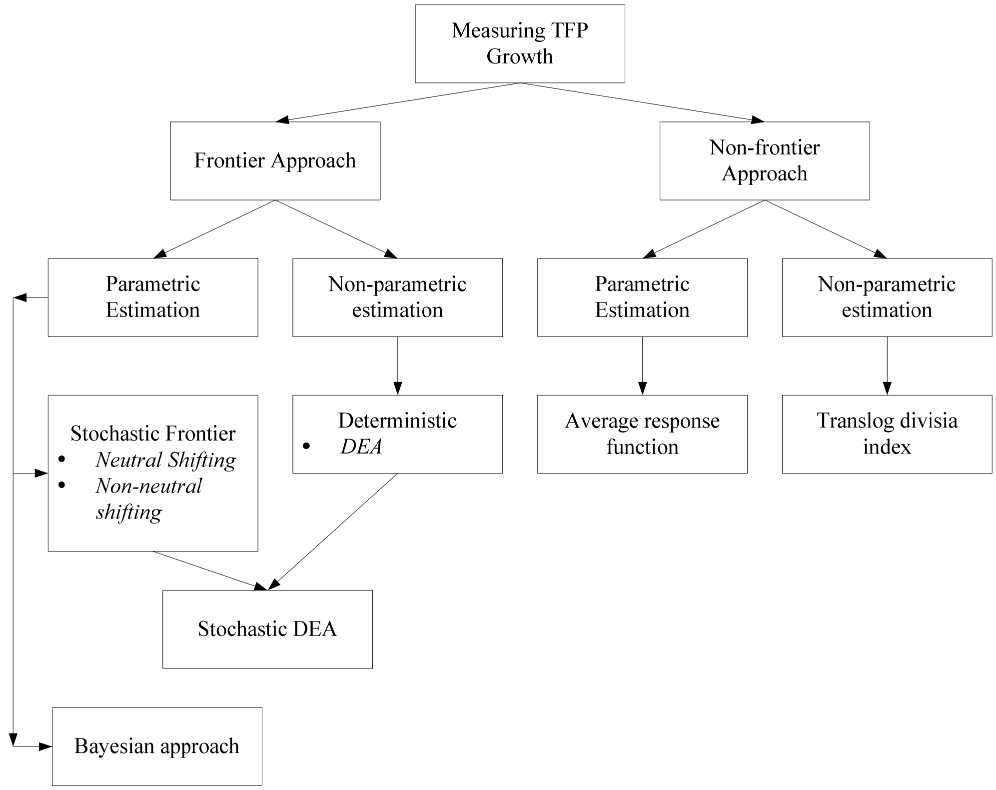
Productivity is associated with the relationship between inputs and outputs, so productivity can be measured by the ratio (Y/X) or the slope of a ray through the origin in Figure 4.2. If the firms move their operations from point A to B, they experience higher levels of productivity because the slope of a ray at point B is greater than at point A. However, by moving from point B to point C, the firms achieve the maximum possible productivity. The movement from point B to point C in the frontier demonstrates the exploitation of scale economies, where the position at point C is the optimal scale operation over any other point along the production frontier. Firms operating at point B are technically efficient, but they may still be able to improve their productivity by utilizing scale economies to achieve the maximum level of productivity at point C. In fact, the changing of scale economies is not a simple and instant process because firms always need time for adjustments. In this case, Coelli et al. (2005) note that technical efficiency and productivity have short-run and long-run perspectives in which the improvement of a firm's productivity in a certain period can be driven by technical efficiency or scale economies, or a combination of these factors.

4.5.2. Methods of Measuring Productivity Growth

According to Coelli et al. (2005), the measure of productivity is essentially a levels concept, and it can be used to compare the performance of firms at a given point in time. Meanwhile, productivity change or growth refers to the movement of a firm's or an industry's productivity performance over time. It is easier to measure productivity if a firm only produces a single output using a single input. However, it is more complex if multiple inputs are used to produce many outputs. Researchers often use a partial productivity measure such as labour productivity, but this measure is potentially misleading and misrepresents the true performance of the firm. Total factor productivity (TFP) is a more appropriate performance measure because it considers multiple inputs-outputs in its formulation.

Mahadevan (2004) summarizes the methods for estimating total factor productivity growth, as presented in Figure 4.3. The early estimations of TFP growth, specifically the non-frontier approach, were pioneered by Abramotivz (1956) and Solow (1957), while studies that use the frontier approach were initiated by Farell (1957). The important terms from Figure 4.3 are frontier and non-frontier and parametric and non-parametric. Most of the recent studies on productivity growth focus on the frontier approach by either applying parametric estimations such as the stochastic production frontier (SPF) or non-parametric estimations such as data envelopment analysis (DEA).

Figure 4.3: Total Factor Productivity (TFP) Estimation Approaches



Source: Mahadevan (2004), p.16

Both methods are the main techniques available for estimating the production frontier, and each method has its own advantages and drawbacks. In this regard, O'Donnell (2011a) explains that the main advantages of DEA are that DEA does not require any explicit assumptions regarding error terms, there are no statistical issues related to multiple input-output technologies, and the computer package is available for computing different measures of efficiency. The main drawbacks of DEA are that DEA does not allow for statistical noise so that it cannot distinguish inefficiency from noise, elasticities of output responses are difficult to compute, measures of reliability for efficiency scores are difficult to compute and sensitive to outliers, and the results tend to be biased if the sample is small.

The main advantage of stochastic frontier analysis (SFA) is that SFA allows errors of approximation and statistical noise so that it is possible to perform statistical inferences. The main disadvantages of SFA are that the result is sensitive to the choice of functional form, for small samples, the results tend to be unreliable, and endogeneity problems are possible in the estimation. If endogeneity exists, the parameters of the production frontier will generally be biased and inconsistent, and a more appropriate approach, such as the generalized method of moments (GMM), is required to solve the endogeneity problem (O'Donnell 2011a). The parametric approach is normally an econometric estimation of a specific model that is based on the statistical properties of error terms, and it allows for statistical testing and validation of the model. The choice of functional form is a crucial stage of estimation because it allows different results. The econometric approach for this estimation is broadly discussed by Khumbakar and Lovell (2000).

Measurement of TFP growth using the deterministic approach is usually performed in the form of an index number. One of the most popular index numbers is the Malmquist TFP Index, as defined by Caves et al. (1982) and based on the distance function proposed by Malmquist (1953). This index is not based on the specific assumptions of the return-to-scale properties of the production technology. All distance functions, either the input-oriented or the output-oriented Malmquist TFP Index, can be computed in the framework of variable returns to scale or constant returns to scale of the technology (Coelli et al. 2005).

The Malmquist index is very popular in the last four decades of research on productivity growth for several reasons. First, it can be computed without requiring any price data; only production data are needed for the estimation. Second, the Malmquist Index can be decomposed into a measure of technical change and technical efficiency change. Finally, the availability of computer software packages that accommodate the computation of the Malmquist TFP Index, such as DEAP2.1, has supported the prominence of the Malmquist Productivity Index (O'Donnell 2011a).

Recently, other alternative productivity indexes that are similar to the Malmquist TFP Index have been developed, such as the Hicks-Moorsteen Index, proposed by Bjurek (1996) and the Färe-Primont Index, proposed by O'Donnell (2010, 2012). Similar to Malmquist, both productivity indexes also require production data.

4.5.3. Färe-Primont Productivity Index

O'Donnell (2010, 2012) proposes a measure of productivity growth that is called the Färe-Primont Productivity Index because it is based on the concept of index measurement created by Färe and Primont. This relatively new index-based measurement of productivity offers a broader perspective on the decomposition of productivity growth. Although the Malmquist Productivity Index is very popular and is used widely in empirical studies, it is actually not complete so that it may be an unreliable measure of TFP growth (O'Donnell 2012)[8]. Unlike Malmquist, the Färe-Primont Productivity Index proposed by O'Donnell (2012) ensures that the terms are "multiplicatively complete", as required by an index measurement approach. All multiplicatively complete TFP indexes can be decomposed into explicit measures of technical change and several identifiable measures of efficiency change.

The Färe-Primont Productivity Index is computed and decomposed using data envelopment analysis (DEA), which also can be run in a computer software package, namely, DPIN 3.0, which has been developed by O'Donnell (2011). This thesis applies the Färe-Primont Productivity Index to compute and decompose TFP growth. The detailed approach is presented in Chapter 6 and Chapter 7 together with the empirical analysis.

4.6. The Effect of Agglomeration Economies on Productivity Growth

The third objective of this thesis is to estimate the effect of agglomeration economies on productivity growth. Therefore, an econometric estimation is performed. TFP growth is regressed against the agglomeration economies variables and other firm or industry characteristics considered as influences on productivity growth. By considering previous studies, such as Glaeser et al. (1992), Dekle (2002), Henderson (2003), and Kuncoro (2009), the basic model in this thesis is written as:

$$TFP_{ijt}=\alpha_0+AGG'_{jt}\beta_1+Z'_{it}\beta_2+D'_j\beta_3+\varepsilon_{ijt} \qquad (4.41)$$

where TFP_{ijt} is a measure of productivity for firm i in region j at time t. The productivity growth in this study is estimated using the Färe-Primont Productivity Index, following O'Donnell (2012). AGG_{jt} represents the agglomeration economies variables of region j at time t, such that AGG consists of LQ (MAR externalities or specialization), DIV (Jacobs' externalities or diversity), and COM (Porter's externalities or competition). Z_{it} represents firm and industry characteristics that include firm age (AGE), firm size (SIZE), and industrial concentration (CR4), while

[8] According to O'Donnell (2012), TFP index is multiplicatively complete if and only if it can be expressed in the form $TFPI(x_t,q_t,x_s,q_s)=[Q(q_t)/X(x_t)]/[Q(q_s)/X(x_s)]$ where $Q(.)$ and $X(.)$ are non-negative non-decreasing linearly-homogenous scalar functions.

D_j is a dummy variable representing urban area (DURB). The parameters to be estimated are β_1, β_2, and β_3. Finally, ε_{ijt} represents the error term.

In this study, MAR externalities are generated by a simple location quotient of employment industry *i* in region *r*. The location quotient and own-industry employment are the most common indicators used to represent the MAR externalities (Beaudry and Schiffauerova 2009). The interpretation is that if $LQ_{ir} > 1$, then the region *r* has a relatively high concentration in industry *i*. In the context of dynamic externalities, it is assumed that knowledge spillovers in industry *i* will be greater when LQ is higher. Theoretically, specialization is hypothesized to positively affect the productivity growth.

In addition, industrial diversity is applied to represent the Jacobs' externalities. As explained by Nakamura and Paul (2009), industrial diversity can be measured by several approaches, such as the inverse of the Hirchman-Herfindahl Index proposed by Duranton and Puga (2000). In general, diversity measures the variety of economic activities that possibly increase the potential cross-industry externalities. If a positive relationship exists between industrial diversity and productivity growth, it represents the Jacobs' externalities.

Meanwhile, Porter's externalities are measured by the ratio of LQ with respect to employment toward LQ with respect to the number of firms, or (LQ employment-based divided by LQ firms-based). If the ratio is greater than one, the region contains relatively large companies or has a monopolistic/oligopolistic environment, and vice versa.

As with most recent studies, this study applies the panel data method and an appropriate model to estimate Equation (4.41). Three models are estimated, namely, the common-effect model or pooled-OLS, the fixed-effects model (FEM within), and the random-effects model (REM) or generalized least squares (GLS) model. To select which model is most suitable, this study applies a simple Chow test (F-test) to test the common-effect model against the fixed-effects model. Greene (2003) explains the procedure of the test, which is written as:

$$F_{[N-1,N(T-1)-K]} = \frac{(R_U^2 - R_R^2)/(N-1)}{(1-R_U^2)/(NT-N-K)} \tag{4.42}$$

where R_U^2 is the R-squared value of the unrestricted model, R_R^2 denotes the R-squared value of the restricted model, N is the number of the firms, T is the time periods, and K is the number of parameters in the unrestricted model. Equation (4.42) states that the H_0 for the F-test is no fixed specific effects, while H_1 is fixed specific effects. If the F-statistic rejects the H_0, the common-effect estimators are biased and inconsistent (Baltagi 2008).

Furthermore, to compare the fixed-effects model and the random-effects model, the Hausman test is applied. This test is based on the chi-square test that refers to the Wald criterion and is expressed as (Greene 2003):

$$W=\chi^2[K-1]=[b-\hat{\beta}]'[Var(b)-Var(\hat{\beta})]^{1}[b-\hat{\beta}] \quad (4.43)$$

where b denotes a vector of estimated parameters from the fixed-effects model, while $\hat{\beta}$ is a vector of the estimated parameters from the random-effects model. $Var(b)$ and $Var(\hat{\beta})$ are variance-covariance matrixes, and W is asymptotically distributed as chi-squared with K degrees of freedom. The H_0 of the Hausman test is that both the fixed-effects model and the random-effects model provide consistent estimators. Conversely, the H_1 stated that only the fixed-effects model provides a consistent estimator, and the random-effects model provides inconsistent estimates. The empirical model in Equation (4.41) is also estimated using the panel dynamic method to enrich the analysis. The detailed estimation method is discussed in Chapter 7, together with the empirical analysis.

4.7. Conclusion

This chapter discusses the empirical methods used in this thesis to examine the effects of agglomeration economies on firm-level productive efficiency and productivity growth. Three main methods are employed to achieve the objectives of the study. First, to examine the effect of agglomeration economies on firm-level productive efficiency, this thesis uses the stochastic production frontier framework, following Battese and Coelli (1995). The inefficiency function, including agglomeration economies variables, is estimated simultaneously with the translog production function under the maximum likelihood technique. Agglomeration economies variables consist of MAR externalities (or specialization), Jacobs' externalities (or diversity) and Porter's externalities (or competition). A set of variables of firm and industry characteristics are also included in the model, namely, firm age, size, market concentration, and two dummy variables representing urban region and industrial complex.

Second, the decomposition of productivity growth is performed by using the Färe-Primont Productivity Index proposed by O'Donnell (2010, 2012). Several methods can be applied to measure and decompose the productivity growth, covering frontier and non-frontier and parametric or non-parametric estimations. Those methods have their own advantages and weaknesses that influence the results of the estimation. The Färe-Primont Productivity Index proposed by O'Donnell (2010, 2012) is a relatively new method that provides broader perspectives on the decomposition of productivity growth than the previous approaches, such as the Malmquist Productivity Index. This index also fills the "multiplicatively complete" axiom, as required in the productivity index formulation. In addition, this approach is also available in the computer package program DPIN 3.0, developed by O'Donnell (2011), which allows the estimation of productivity change and levels and the possibility of identifying firms or industries that achieve the maximum productivity level.

Finally, to investigate the impact of agglomeration economies on productivity growth, this thesis employs the estimation framework of panel data for both the static model or for the dynamic model. Productivity growth, as the main target, is regressed on the agglomeration economies and on a set of variables that comprise firm and industry characteristics, as discussed previously. The detailed empirical analysis is conducted in the following chapters, specifically, Chapters 5, 6 and 7.

Chapter 5
The Effect of Agglomeration Economies on Firm-Level Productive Efficiency

5.1. Introduction

As discussed in Chapter 3, agglomeration economies are recognized as one of the important factors that affect firms' productivity growth. However, the results from empirical studies are inconclusive. Therefore, this topic continues to be debated among scholars. The differential effects of agglomeration economies upon productivity growth are the results of methodologies used in the study, especially the choice of performance measures, the indicators of agglomeration economies, and whether industrial or geographical aggregation is considered (Beaudry and Schiffauerova 2009). The analysis on the effect of agglomeration economies on firms' productivity using appropriate method and accomodating specific characteristic of firm and industry is expected to provide a substantial contribution to this subject.

From the perspective of industrial policy, the contribution of agglomeration economies upon firms' productivity growth is an important feature, because industrial agglomeration has been recognized as a common characteristic of economic activity in both developed and developing countries. Agglomeration economies are considered as the crucial part of development policy in many countries. A comprehensive analysis of this phenomenon is expected to contribute to better policies for industrial and regional development.

Chapter 5 is the first empirical analysis of this thesis, which examines the effect of agglomeration economies on firm-level technical efficiency or firms' productive efficiency. Technical efficiency is one source of total factor productivity (TFP), in which TFP growth can be decomposed into three components namely technical change, scale efficiency change and technical efficiency change (Kumbhakar and Lovell 2000; Coelli et al. 2005). As discussed in Chapter 4, to measure firm-level technical efficiency, this study adopts the multiple inputs approach. Furthermore, the effect of agglomeration economies upon firm-level technical efficiency is estimated using the stochastic production frontier (SPF) approach following Battese and Coelli (1995).

The remainder of this chapter is organized as follows. Section 5.2 discusses the empirical model and estimation method, followed by definition and measurement of variables in Section 5.3. Section 5.4 discusses the data set used in this study. Section 5.5 analyses and interprets the empirical results. Concluding remarks and policy implications are given in Section 5.6.

5.2. Empirical Model and Estimation Method

As described in Chapter 4, to analyse the effect of agglomeration economies upon firm-level technical efficiency, this study applies one-stage stochastic frontier model proposed by Battese and Coelli (1995). To estimate the parameters of the stochastic frontier model, a proper functional form needs to be specified prior to estimation. Salim (2004) argues that the choice of the functional form is crucial for modelling the data, as different model specifications can give rise to very different results. In relation to the production function, various functional forms can be applied, such as linear, Cobb-Douglas, quadratic, normalised quadratic, translog, generalised Leontief, and constant elasticity of substitution (Salim 1999). Of these existing functional forms, transcendental logarithmic (translog) and Cobb-Douglas are the two most common models used in the empirical research, including frontier analysis (Battese and Broca 1997).

Following Suyanto (2010), this study starts with a flexible translog production frontier. The translog production function is first introduced by Christensen et al. (1972). There are at least three reasons why this model is preferred. First, the translog functional form provides some generality as it requires fewer restrictions on the structure of production (Kopp and Smith 1980). Second, the translog allows for non-constant returns to scale as well as for technical changes to be both neutral and factor augmenting (Feser 2002). Finally, partial elasticities among inputs of production can vary, while the elasticity of scale can vary with output and input proportions (Feser 2002). The application of the translog form also reduces the error in model specification and allows for the decomposition of productivity growth.

In addition, there are several reasons for applying a frontier approach. As pointed out by Mahadevan (2004), the first reason is that the frontier is an unobservable function that is said to represent the "best practice" function, as it bounds or envelopes the sample data. Second, the frontier approach identifies the role of technical efficiency in overall firm performance. Finally, the frontier TFP growth consists of outward shift of the production function resulting from technological progress due to technological improvements incorporated in inputs, as well as technical efficiency movement toward the production frontier.

The functional form of the translog production frontier used in this study can be written as follows:

$$\begin{aligned} \ln y_{it} = {} & \beta_0 + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_M \ln M_{it} + \beta_E \ln E_{it} + \beta_{LL}[\ln L_{it}]^2 + \beta_{LK}[\ln L_{it} * \\ & \ln K_{it}] + \beta_{LM}[\ln L_{it} * \ln M_{it}] + \beta_{LE}[\ln L_{it} * \ln E_{it}] + \beta_{KK}[\ln K_{it}]^2 + \\ & \beta_{KM}[\ln K_{it} * \ln M_{it}] + \beta_{KE}[\ln K_{it} * \ln E_{it}] + \beta_{MM}[\ln M_{it}]^2 + \beta_{ME}[\ln M_{it} * \\ & \ln E_{it}] + \beta_{EE}[\ln E_{it}]^2 + \beta_t t + \beta_{Lt}[\ln L_{it} * t] + \beta_{Kt}[\ln K_{it} * t] + \beta_{Mt}[\ln M_{it} * \\ & t] + \beta_{Et}[\ln E_{it} * t] + \beta_{tt} t^2 + v_{it} - u_{it} \qquad (5.1) \end{aligned}$$

where y is output, L is labour, K is capital, M is raw material, E is energy, *t* is time, *i* is firm, *β's* are parameters to be estimated, *ln* denotes natural logarithm, v_{it} is the stochastic error term, and u_{it} is technical inefficiency. In this model, the technical inefficiency effect is a function of agglomeration economies variables plus firm and industry characteristics. Following Glaeser et al. (1992), agglomeration economies used in this estimation include specialization or MAR externalities (LQ), diversity or Jacobs' externalities (DIV), and competition or Porter's externalities (COM). In addition, firm and industry characteristic variables that included in the model are firm age (AGE), firm size (SIZE), market/industrial concentration ratio (CR4), and two dummy variables representing urban area (DURB) and industrial area/complex (DLOC). The technical inefficiency function can be expressed as:

$$\begin{aligned} u_{it} = {} & \delta_0 + \delta_1 LQ_{it} + \delta_2 DIV_{it} + \delta_3 COM_{it} + \delta_4 AGE_{it} + \delta_5 SIZE_{it} + \delta_6 CR4_{it} + \\ & \delta_7 DLOC_{it} + \delta_8 DURB_{it} + w_{it} \qquad (5.2) \end{aligned}$$

where w_{it} is an error term.

Some hypotheses for the translog functional form in Equation (5.1) are to be tested. First, the hypothesis to test whether the Cobb-Douglas frontier is appropriate for the data set ($\beta_{LL}=\beta_{LK}=\beta_{LM}=\beta_{LE}=\beta_{KK}=\beta_{KM}=\beta_{KE}=\beta_{MM}=\beta_{ME}=\beta_{EE}=0$). Second, the hypothesis for Hick-neutral technological progress $(\beta_{Lt}=\beta_{Kt}=\beta_{Mt}=\beta_{Et}=0)$. Third, the hypothesis for no technological progress in the frontier $(\beta_t=\beta_{tt}=\beta_{Lt}=\beta_{Kt}=\beta_{Mt}=\beta_{Et}=0)$ and, fourth, the hypothesis for a no-inefficiency effect is $(\gamma=\delta_0=\delta_1=\ldots=\delta_8=0)$.

According to Battese and Coelli (1995), if $\gamma=0$, the model reduces to a traditional mean response function in which random factor variables affecting technical inefficiency can be directly included in the production frontier. To test the hypotheses above, a generalized likelihood ratio statistic is applied. This ratio statistic can be expressed as:

$$\lambda=-2\left[l(H_0)-l(H_1)\right] \tag{5.3}$$

where $l(H_0)$ denotes the value of likelihood function based on the null hypothesis or the restricted frontier model and $l(H_1)$ is the value of likelihood function in the alternative hypothesis or model defined in Equation (5.2).

The stochastic production frontier in Equation (5.1) and the technical inefficiency function in Equation (5.2) can be estimated simultaneously in one-stage using the computer program FRONTIER 4.1 under the maximum likelihood method. As described by Coelli (1996), this program follows a three-step estimation method to obtain the final maximum likelihood estimates. First, ordinary least square (OLS) estimates of the function are obtained. All β estimators, with the exception of the intercept, will be biased. Second, a two-phase grid search of γ is conducted, with the β parameters (excepting β_0) set to the OLS values and the β_0 and σ^2 parameters adjusted according to the corrected ordinary least square formula presented in Battese and Coelli (1995). Any other parameters (μ, η, or δ's) are set to zero in this grid search. Third, the values selected in the grid search are used as starting values in an interactive procedure (using the Davidson-Fletcher-Powell Quasi-Newton method) to obtain the final maximum likelihood estimates.

5.3. Definition and Measurement of Variables

The definition and measurement of the variables used in the model is a very important stage in the estimation of the production function. This is to ensure the accuracy, consistency and reliability of the data, and to avoid biased analysis. Previous studies varied significantly in the selection of variables used in the model.

Battese and Coelli (1995) argue that the technique used in the generation of variables should be used in conjunction with carefully compiled data for input and output quantities and prices. A set of variables to be used in the empirical model is developed; including variables of the stochastic production frontier (Equation 5.1) and technical inefficiency function (Equation 5.2). The definitions of these variables are listed in Table 5.1.

5.3.1. Variables in Production Frontier

As in numerous studies, this thesis uses gross output as the dependent variable and labour, capital, raw materials, and energy as the independent variables of the stochastic production frontier. Details of these variables are given in the following sub-sections.

5.3.1.1. Output (Y)

Empirically, two types of data are commonly used as dependent variables for the estimation of TFP growth, namely gross output and value added. However, which one is better, is still contested among scholars (Mahadevan 2004). There are arguments to support the use of each. Diewert (2000), for example, argues that to compare TFP growth at the industry level, the use of value-added data is better than the use of output, because the latter includes the purchase of intermediate inputs, which may vary greatly among industries.

However, there is criticism of the use of the value-added as dependent variable, such as that put forward by Oulton and O'Mahony (1994). They suggest that in reality nothing resembles value-added because firms do not produce goods in units of value added. Most studies on productivity growth in Indonesia use output as the dependent variable of the production function, such as Pitt and Lee (1981), Margono and Sharma (2006), Ikhsan (2007), and Suyanto et al. (2009).

Table 5.1: Definition of Variables Used in the Model

Variables	Definition
Production Function	
Y	Total value of output in rupiahs, deflated by the wholesale price index (WPI) for 2-digit ISIC level at constant market for the year 2000
L	Number of labour (persons), consisting of production worker and non-production worker
K	Capital expenditure in rupiahs, deflated by the WPI for 2-digit ISIC level at constant market for the year 2000
E	Energy expenditure in rupiahs: the total sum of electricity and fuel expenditure. The expenditure for electricity is deflated by the electricity price index for industrial sector and fuel expenditure is deflated by the WPI of fuels for 2-digit ISIC level at constant price for the year 2000
M	Raw material expenditure in rupiahs, deflated by the WPI for 2-digit ISIC level at constant market price for the year 2000
Inefficiency Function	
LQ (specialization)	Specialization index, measured by Location Quotient (LQ)
DIV (diversity)	Diversity index, measured by the inverse of the Hirchman-Herfindahl Index (HHI)
COM (competition)	Competition index, measured by the ratio of the specialization index (LQ) in terms of number of firms and LQ in terms of number of employees.
AGE	Firm age, measured by number of years from the firm's establishment to this survey.
SIZE	Firm size, measured by number of workers including production and non-production.
CR4	Industrial concentration, measured by value added share of four largest firms in 2-digit ISIC level.
DURB	Dummy variable to represent urban and non-urban regions.
DLOC	Dummy variable to represent location of firms, inside or outside industrial area/complex.

By considering the terminology of firm output used by the Statistics Indonesia *(Badan Pusat Statistik - BPS)* and previous studies as discussed above, this study uses the total value of output as the dependent variable. According to BPS's definition, the composition of output is dominated by the value of goods produced, which is around 80 percent of total value of output. The use of output is more appropriate because, in essence, the nature of the production function reflects the firm production process. Since the value of output is in terms of market value, it needs to be deflated the value to a constant price. In this study, the wholesale price index (WPI) of manufacturing industries for 2-digit ISIC level is used to deflate into constant price for the year 2000.

5.3.1.2. Labour (L)

In addition to capital, labour is very important in the production process because it constitutes a major component of the total expenditure on inputs in many companies. Coelli et al. (2005) state that the quantity of the labour input is normally measured using a single aggregate variable. The most frequently-used measures of labour inputs are: number of person employed, number of hours of labour inputs, number of full-time equivalent employees, and the total wages and salaries bill.

As this study is conducted at the firm level, the total number of employees is used in the estimation of the frontier production function; this includes the number of production workers and non-production workers. Most previous studies on this subject in Indonesia use this variable in their analysis, such as those of Takii (2004), Jacob and Meister (2005), Vial (2006), Ikhsan (2007), Margono and Sharma (2006), Suyanto et al. (2009) and Kuncoro (2009). However, Pitt and Lee (1981) use wages payments and man-months of labour.

5.3.1.3. Capital (K)

A proper measurement of capital in the efficiency and productivity studies is very crucial. Measuring the quantity and price of capital is difficult. The main reason is that capital is a durable input which differs from labour and raw materials. Conceptually, there are some methods can be used to measure capital, such as the perpetual inventory method (PIM), replacement values, or sales values of assets. Capital is defined as the total services flow from various capital assets of the firm. Assets can refer to buildings, land, machineries, vehicles and other equipment that has the potential to provide services over a period of time (Coelli et al. 2005).

The Indonesian manufacturing data does not directly indicate the capital stock. Based on the availability of the data provided by the BPS, in this study capital is measured by the summation of fixed capital, which consists of the value of buildings, lands, machineries, vehicles and other fixed capital, plus the difference in inventory value at the end and at the beginning of the year. The capital is deflated to a constant value by WPI of 2-digit ISIC manufacturing industries for the year 2000.

5.3.1.4. Material (M)

Materials account for a substantial share of the production inputs in the most manufacturing industries. Material in this study is measured by the value of raw and intermediate materials domestically produced and imported. The real value of materials is obtained by deflating the nominal value using the WPI of 2-digit ISIC manufacturing industries at constant price for the year 2000.

5.3.1.5. Energy (E)

As with raw materials, energy inputs constitute a significant share of the input costs in many manufacturing industries. In this study, two types of energy are used in the estimation. First is electricity, which includes the electricity provided by the State Electricity Company *(Perusahaan Listrik Negara – PLN),* and the electricity provided by private companies. Most Indonesian manufacturing companies use electricity provided by PLN, but in some cases they also use electricity from private sources, especially for the large companies. To obtain the real value of electricity, the nominal value is deflated by the wholesale electricity price index provided by PLN.

In addition, six types of fuels must be considered, namely gasoline, diesel fuel, diesel oil, fuel oil, lubricant, and other fuels including kerosene, coal, coke, gas from the state company, and liquid petroleum gas (LPG). The real value of fuels is obtained by deflating the nominal value with the fuel price index published by BPS at constant market price for the year 2000. The total value of energy is obtained from by summing the real value of electricity and the real value of fuels.

5.3.2. Agglomeration Economies Variables

Referring to Equation (5.2), the main variables in the technical inefficiency function are agglomeration economies. Following Glaeser et al. (1992), agglomeration economies variables to be analysed in this study include Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity), and Porter's externalities (or competition). The conceptual underpinnings of these variables are described in the following sub-sections.

5.3.2.1. MAR Externalities or Specialization (LQ)

MAR externalities or specialization are concerned with the knowledge spillovers between firms in a specific industry. As discussed in Chapter 3 and Chapter 4, the regional specialization of an industry can be measured by location quotient (LQ) (Henderson et al.1995; Glaeser et al. 1992). Beaudry and Schiffauerova (2009), in their meta-analysis, empahsize that LQ is the most frequently applied indicator for measuring specialization. LQ shows the relative size of economic activity in a particular region (representated by sectoral labour share) compared to the national level. Following Nakamura and Paul (2009), as described in Chapter 4, the regional specialization index is defined as the share of industry *i's* employment relative to total industry employment in a specific region *j*, compared to the share of region *j's* employment relative to total (national) employment in industry *i*. Recall back from Equations (4.30) to (4.33) in Chapter 4, the specialization level (denoted S) in region *j* with respect to industry *i* is given by:

$$S_{ij}^{S}=\frac{X_{ij}}{\sum_{i=1}^{I}X_{ij}}=\frac{X_{ij}}{X_{*j}},\ i=1,\ldots,I;j=1,\ldots,J, \tag{5.4}$$

In Equation (5.4), the denominator shows the aggregated over industries. Further, at a national level industrial composition is represented by:

$$S_{i*}=\frac{\sum_{j=1}^{J}X_{ij}}{\sum_{i=1}^{I}\sum_{j=1}^{J}X_{ij}}=\frac{X_{i*}}{X_{**}}, \tag{5.5}$$

so the regional specialization index relative to national industrial composition can be expressed as:

$$LQ_{ij}^{S}=\frac{S_{ij}^{S}}{S_{i*}}=\frac{X_{ij}/X_{*j}}{X_{i*}/X_{**}},\ i=1,\ldots,I \tag{5.6}$$

That is, this form of location quotient represents the specialization of industry *i* in region *j* relative to the specialization of industry *i* in all regions.

The average of these location quotients across industries can be expressed as:

$$LOC_{j}^{S}=\frac{1}{I}\sum_{i=1}^{I}\frac{S_{ij}^{S}}{S_{i*}}, \tag{5.7}$$

where $LOC_{j}^{S}>1$ indicates a high relative level of regional specialization for region *j*. This parameter measures how specialized a region is in a particular industry relative to the national level (Glaeser et al. 1992). In the context of dynamic externalities, it is assumed that knowledge spillovers in industry *i* will be greater when LQ is higher. Theoretically, industrial specialization is hypothesized to be positively associated with regional-industrial efficiency. Moreover, Nakamura and Paul (2009) explain that although LQ is generally measured in terms of labour, however, it can also be measured by using other indicators such as number of firms or output of industry. In this study, LQ is measured in terms of labour.

5.3.2.2. Jacobs' Externalities or Diversity (DIV)

Regional diversity is another crucial agglomeration indicator associated with the variety of economic activities (Nakamura and Paul 2009). Industrial diversity is expected to increase the potential for externalities in the local industry and for cross-industry. As discussed in Chapter 4, Jacobs (1969) argues that a variety of geographically proximate industries will promote innovation and growth rather than geographical specialization. This differs from the view of MAR externalities. One of the approaches which can be used to measure the regional diversity or Jacobs' externalities is the inverse of the Hirchman-Herfindahl Index (HHI) in terms of regional specialization, as proposed by Duranton and Puga (2000). Recall back from Equation (4.36) in Chapter 4, the formula can be written as:

$$DIV_j^A = 1 \Big/ \sum_{i=1}^{I} (S_{ij}^S)^2 , \qquad (5.8)$$

where DIV_j^A takes a value of I (the number of industries in the industrial classification) if industrial employment in region j is evenly distributed among all industries, i.e. maximum diversification (Nakamura and Paul 2009). In general, industrial diversity measures the variety of economic activities, which can increase the potential number of cross-industry externalities. If a positive relation exists between industrial diversity and industry efficiency, this represents Jacobs' externalities.

5.3.2.3. Porter's Externalities or Competition (COM)

Porter argues that local competition will accelerate imitation and the improvement of innovators' ideas. Competition creates a pressure for firms to innovate more and firms that do not advance technologically will be excluded from the market or industries. Porter believes that competition among local firms leads to the innovations of others being adopted and improved upon, and so generates industry efficiency (Glaeser et al. 1992).

Following Nakamura and Paul (2009), the degree of competition in this study is measured by the ratio of the employment (labour)-based location quotient $(LQ_{ij}^{S(E)})$ to the plant (firm)-based location quotient ($LQ_{ij}^{S(P)}$).[9] Therefore, if $LQ_{ij}^{S(E)} > LQ_{ij}^{S(P)}$, so that the ratio is greater than one, region *j* contains relatively large plants or has a monopolistic/oligopolistic regional environment. However, if $LQ_{ij}^{S(P)} > LQ_{ij}^{S(E)}$, so that the ratio is less than one, region *j* contains relatively small plants or has a competitive regional environment.

5.3.3. Other Variables Affecting Firm-level Technical Efficiency

In addition to agglomeration economies variables, other variables may also affect a firm's technical efficiency. Among the potential variables, this study uses several firm and industry level features, namely firm age (AGE), firm size (SIZE), market/industrial concentration ratio (CR4), and two dummy variables representing urban area (DURB) and industrial complex/industrial area (DLOC). The following sub-sections describe these variables.

5.3.3.1. Firm Age (AGE)

Firm age is expected to be a factor that influences the efficiency of firm because it relates to the firm's learning process and adaptation to the environment. Numerous previous studies such as Henderson (1986), Battese and Coelli (1995), and Suyanto et al. (2009) use this variable in their estimation model. However, the impact of age upon firm-level technical efficiency remains debated among scholars. There are two sides of arguments. According to Arrow (1962), older firms tend to have more learning experience than younger firms, so that they run their operation and production more efficiently. Older firms have experience in handling management and surviving in unfavourable economic conditions. A contrary argument is proposed by Teece (1986) and Winter (1987). They argue that younger firms possibly have an advantage in the area of knowledge, and the use of modern technology and sophisticated machinery. Moreover, younger firms tend to give more attention to research and development. With these conditions, it is claimed that younger firms can reach higher level of efficiency than older firms.

[9] Based on Equation (5.6), employment-based location quotients is measured as $LQ_{ij}^{S(E)} = \frac{S_{ij}^{S}}{S_{i*}} = \frac{X_{ij}/X_{*j}}{X_{i*}/X_{**}}$, $i=1,...,I$, and plant-based location quotients is measured as $LQ_{ij}^{S(P)} = \frac{S_{ij}^{S}}{S_{i*}} = \frac{X_{ij}/X_{*j}}{X_{i*}/X_{**}}$, $i=1,...,I$. Local competition is measured by ratio of $LQ_{ij}^{S(E)} / LQ_{ij}^{S(P)}$.

In the empirical analyses, there are also different findings. The positive impact of age upon firm efficiency level can be seen, for example, in Chen and Tang (1987), Haddad (1993) and Suyanto et al. (2009), while the negative impact can be seen in Pitt and Lee (1981) and Hill and Kalirajan (1993). The other finding is that a firm's age has no significant impact on its efficiency; see, for example, Kathuria (2001) and Jacob and Meister (2005). Based on these empirical results, we can conclude that the impact upon age to firm efficiency remains controversial.

In this study, firm's age is measured by the number of years of production, which are calculated from the first time the firm operated or established in the relevant region. The year of firm establishment is provided by the BPS in a specific manufacturing survey.

5.3.3.2. Firm Size (SIZE)

In the simple relationship of structure–conduct–performance (SCP), firm size is recognized as an important factor that affects firm performance, such as productivity level. The reason is that a bigger firm tends to have a higher market share and ultimately, it will generate market power that allows it to control the market. Salim (2008) mentions that firm size also reflects the existence of scale economies, so that the larger firm size tend to has the lower unit cost of production. Conceptually, firm size is close to market share but it differs in the way it is measured. Market share tends to be associated with the external environment while firm size tends to be a product of a firm's own characteristics.

Firm size has been used in a range of empirical research, such as that conducted by Pitt and Lee (1981), Margono and Sharma (2006), Wheeler (2006), Kalkulis (2010), and Lee et al. (2010). Size can be measured using various proxies, depending on the data availability and research purposes. Pitt and Lee (1981) use the number of workers to represent the size of firm. In addition, Margono and Sharma (2006), Figueiredo et al. (2009), and Kalkulis (2010) also use labour as proxy, but with a slightly different definition.

In this study, firm size is measured by the total number of employees includes production and non-production employees. Larger firms are expected to have a higher level of firm efficiency than smaller firms, as the former can normally control the market.

5.3.3.3. Industrial Concentration (CR4)

The important influence of industrial concentration upon firm-level technical efficiency can also be seen through the simple relation of structure–conduct–performance (SCP). Conceptually, firms' technical efficiency is included as one of the firm performance indicators, so that its relationship with industrial concentration can be examined. In this study, industrial concentration is measured by the concentration ratio of four largest firms (CR4) in each industry, based on the 2-digit ISIC level.

CR4 typically measures the market structure and level of competition in each industry. The higher value of CR4 indicates higher level of oligopolistic or monopolistic market structure. The level of competition between firms in particular industry will affect the firm-level technical efficiency. In Indonesia, industrial concentration is a crucial phenomenon. It receives deep attention from the government specifically after some academic investigations conducted in the mid-1990s. High industrial concentration is considered as the one source of market inefficiency. Among other places, an analysis of this issue can be found in Bird (1999). In general, most sub-sectors industries at 2-digit ISIC level have oligopolistic market structure. A group of businesses dominates certain industries and, in most cases, they receive special privileges from the government.

5.3.3.5. Dummy Variable for Urban Region

Regional disparity, more specifically between urban and non-urban areas is an important characteristic of regional development in Indonesia. Typically, a few regions are highly developed with high income per-capita while other regions tend to be left behind or less developed. The Island of Java is the centre of economic activities, with its share of national output around 80 percent. The disparity is not only at the national level but also in the lower level of the government such as province and regency.

The level of regional development and the existence of urban and non-urban areas are essential in stimulating the performance of firms. The availability of good and adequate infrastructure attracts firms to locate in an urban area. Such facts are consistent with the theory of agglomeration, which claims that one of the reasons companies concentrate in a close region is the easy access to inputs of production and the availability of adequate infrastructure (Marshall 1920). In addition, urban features such as the potential of market access and population size are also key factors in driving regional growth (Duranton and Puga 2004). Urban regions may also facilitate inter-firm knowledge spillovers. Given this, it is important to investigate the contribution of urban areas to a firm-level technical efficiency.

Most studies on agglomeration and regional development in Indonesia apply a dummy variable to distinguish the impact of regional development on a region's growth and on firm productivity levels. The regional level used in these studies are varies from regency (municipality) to provincial level, or the model focus on a particular group of regions. Among these studies, for example, are Kuncoro (2009) and Kuncoro and Wahyuni (2009).

In this study, the dummy variable for urban areas is applied for selected municipalities or cities that contribute substantially to manufacturing output. There are 34 selected municipalities and cities, representing urban areas from 497 regions in Indonesia in 2009. These selected regions contribute around 80 percent to Indonesia's total manufacturing output.

5.3.3.6. Dummy Variable for Industrial Area/Complex

The presence of industrial area or industrial complex is another important aspect in the discussion of industrial agglomeration. The basic nature of industrial complex is similar to the concept of an industrial district, central business district (CBD), or industrial park. Firms in an industrial complex allow interacting more intensively. As argued by Henderson (2003), industrial complex leads to the spatial proximity of firms and facilitates knowledge spillovers. The local knowledge accumulation then affects the productivity of the local firm.

In Indonesia, the establishment of industrial complexes represents a specific industrial policy implemented by the government. The aim is to accelerate industrial development by providing better facilities in selected regions. With this policy, the government intends to concentrate firms in a particular complex so that inter-firm spillovers are achieved rapidly. The establishment of industrial complex follows the success of industrial areas in many countries, such as Silicon Valley in the U.S. The first such policy was introduced in 1983. However, the policy has become more popular and received greater attention from the government after the medium- and long-term industrial development policies released in 2001 and 2004.

Table 5.2 contains a summary of the estimation model discussed above. The table shows the expected effects of input variables in the translog production frontier and of exogenous variables in the technical inefficiency model.

Table 5.2: Expected Signs of Parameter Estimates of the Stochastic Production Frontier (SPF)

Variables	Expected sign
Production Frontier *(dependent variable: lnY)*	
L (ln)	+
K (ln)	+
M (ln)	+
E (ln)	+
Inefficiency function *(dependent variable: u)*	
LQ (specialization)	-
DIV (diversity)	+
COM (competition)	+
Age (firm age)	+/-
SIZE (firm size)	-
CR4 (concentration ratio)	+
DURB (dummy urban area)	-
DLOC (dummy location)	-

Note: + indicates positive effect, - indicates negative effect, +/- indicates inconclusive effect.

5.4. Data

The data used in this chapter is the statistics of medium and large manufacturing industry provided by Statistics Indonesia *(Badan Pusat Statistik – BPS)*. By considering the availability and the limitation of data information, such as the information of industrial complex, the period of analysis in this chapter is chosen from 2004 to 2009. The detail of variables description and the data cleaning procedure to create a balanced panel data used in this estimation is presented in the Appendix 5.1 and 5.2.

5.5. Results and Interpretation

5.5.1. Testing for Model Specification

Testing for the model specifications is applied to ensure the estimation model fills the assumptions of general translog frontier specification, as mentioned in the previous section. This is a standard procedure in research using the translog production function. The testing results are presented in full in Table 5.3.

Table 5.3: Log-Likelihood Tests for Model Specification of the Stochastic Production Frontier

Restrictions	Model 1	Model 2	Model 3	Critical Value		
				(α=0.10)	(α=0.05)	(α=0.01)
Cobb-Douglas ($\beta_{LL}=\beta_{LK}=\beta_{LM}=\beta_{LE}=\beta_{KK}=\beta_{KM}=\beta_{KE}=\beta_{MM}=\beta_{ME}=\beta_{EE}=0$)	7706.76[a)]	7706.76[a)]	7706.76[a)]	15.98	18.30	23.20
Hicks-Neutral ($\beta_{LT}=\beta_{KT}=\beta_{MT}=\beta_{ET}=0$)	11.76[b)]	11.76[b)]	11.76[b)]	7.78	9.49	13.28
No-Technological Progress (TP) ($\beta_{T}=\beta_{TT}=\beta_{LT}=\beta_{KT}=\beta_{MT}=\beta_{ET}=0$)	31.14 [a)]	31.14 [a)]	31.14 [a)]	10.64	12.59	16.81
No-Efficiency Effect ($\gamma=\delta_0=\delta_1=\cdots\delta_8=0$)	1063.44[a)]	1069.58 [a)]	1085.69 [a)]	7.09	8.76	12.48

Note: [a)], [b)], and [c)] denote 1%, 5%, and 10% significance level, respectively. The Log-likelihood ratio statistics are calculated from the equation for the translog-production frontier, based on the restricted and unrestricted models. The critical values are based on the Chi-squared distribution. For the null hypothesis of a no-inefficiency effect, the critical value is based on a mixed chi-squared distribution provided by Kodde and Palm (1986).

The first null hypothesis is to check whether the Cobb-Douglas production frontier is an appropriate model for the dataset, by imposing the restrictions (β_{LL}=β_{LK}=β_{LM}=β_{LE}=β_{KK}=β_{KM}=β_{KE}=β_{MM}=β_{ME}=β_{EE}=0) on Equation (5.1). The result of the log-likelihood test indicates a strong rejection of the null hypothesis at the 1% level of significance for the full samples set, implying that the Cobb-Douglas model is an inappropriate specification, given the translog production frontier. The second null hypothesis is to confirm Hicks-neutral technological progress (TP) with the restriction (β_{Lt}=β_{Kt}=β_{Mt}=β_{Et}=0). The results also reject the null hypothesis for the full sample set but at the 5% significance level. The third null hypothesis imposes a restriction (β_{t}=β_{tt}=β_{Lt}=β_{Kt}=β_{Mt}=β_{Et}=0) for no-technological progress (TP). The test result shows the rejection of the null hypothesis at the 1% significance level, meaning that the no-TP specification is not appropriate, given the translog production frontier. The last hypothesis is to confirm the no technical efficiency effect by applying the restriction: (γ=δ_0=δ_1=...=δ_8=0). The test result shows the rejection of the null hypothesis at the 1% significance level for full sample set. The last hypothesis test was applied for three different specifications of the technical inefficiency equation, and the result for each was in the same direction.

Based on the null hypothesis results, it can be concluded that the flexible translog model, as specified in Equation (5.1), is the appropriate model for the full sample.

Therefore, the estimation of the stochastic frontier in this chapter follow the translog production frontier.

5.5.2. Technical Efficiency: Empirical Results

In this research, three different models are estimated to observe the effect of agglomeration economies and other relevant factors upon firm-level technical efficiency. The first model focuses on the influence of two agglomeration economies variables namely specialization (or MAR externalities) and diversity (or Jacobs' externalities). As discussed in Chapter 4, both variables of agglomeration economies have been historically debated among scholars, especially their contribution to economic and productivity growth, such as explained in Glaeser et al. (1992) and Henderson (2003). The empirical results of this issue have been mixed, and it depends on the circumstances and methodologies applied (Beaudry and Schiffauerova 2009).

In the second model, variable of competition (or Porter's externalities) is added. This is another important variable of agglomeration economies. In the third model, firm and industry characteristics that considered as factors affected firm-level technical efficiency are added. The variables include firm age (AGE), size (SIZE), and industrial concentration (CR4). Meanwhile, two dummy variables representing urban area and industrial complex are included in all models. To see whether a serious multicolinearity exists or not, Table 5.4 shows the correlation value of these variables.

Table 5.4: Correlation between Variables in the Technical Inefficiency Model

	LQ	DIV	COMP	AGE	CR4	SIZE	DURB	DLOC
LQ	1							
DIV	0.4496	1						
COMP	-0.1032	0.2325	1					
AGE	-0.0071	-0.0133	-0.0335	1				
CR4	0.0630	0.1306	0.0414	0.0597	1			
SIZE	0.0053	-0.0498	0.0740	0.1016	0.0171	1		
DURB	0.3467	0.2963	0.1754	0.0436	0.0346	0.2216	1	
DLOC	0.0328	0.0033	0.0489	-0.0410	0.0027	0.158	0.1412	1

The table indicates that no serious correlation occurs, as all the correlation scores among these variables are quiet low. Finally, the full estimation results for the three different models are presented in Table 5.5. The estimation results for the three models show a consistent direction for both coefficients in the main production function or in the technical inefficiency function. The interpretation of the estimation results begins with an analysis of the coefficient of production inputs. Further discussion and analysis on the effect of agglomeration economies on firm-level technical efficiency refer to Model 3 as the estimation function for the full set. The coefficients for labour, capital, raw materials, and energy are 0.8414, 0.0510, 0.0603, and 0.2657 respectively. The sign is positive as posited in the hypothesis, indicating that an increase in production inputs will increase production output. This estimation result is mostly in line with previous research in Indonesia, such as that of Pitt and Lee (1981), Battese et al. (2001), Margono and Sharma (2006), Ikhsan (2007) and Suyanto et al. (2009). The one difference is the magnitude of the coefficient, where by labour contributes most substantially.

Table 5.5: The Estimation Results of the Production Frontier Model, 2004–2009

Variables	Parameters	Model 1		Model 2		Model 3	
		Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Production function (dep var: LnY)							
Constant	β_0	4.3677	46.96[a)]	4.3777	48.43[a)]	4.4847	48.70[a)]
T	β_T	0.0312	2.54[a)]	0.0324	2.71[a)]	0.0347	2.82[a)]
Ln(L)	β_L	0.8415	34.05[a)]	0.8434	33.97[a)]	0.8414	35.48[a)]
Ln(K)	β_K	0.0503	5.46[a)]	0.0493	5.72[a)]	0.0510	5.50[a)]
Ln(M)	β_M	0.0776	5.87[a)]	0.0692	5.34[a)]	0.0603	4.54[a)]
Ln(E)	β_E	0.2654	23.00[a)]	0.2732	24.55[a)]	0.2657	22.98[a)]
$[Ln(L)]^2$	β_{LL}	0.0448	15.12[a)]	0.0452	15.38[a)]	0.0448	16.25[a)]
Ln(L)* Ln(K)	β_{LK}	0.0135	7.53[a)]	0.0134	7.43[a)]	0.0135	7.34[a)]
Ln(L)* Ln(M)	β_{LM}	-0.0912	-36.41[a)]	-0.0915	-37.30[a)]	-0.0907	-36.70[a)]
Ln(L)* Ln(E)	β_{LE}	0.0076	3.22[a)]	0.0076	3.26[a)]	0.0065	2.77[a)]
$[Ln(K)]^2$	β_{KK}	0.0085	19.70[a)]	0.0085	19.58[a)]	0.0084	20.62[a)]
Ln(K)* Ln(M)	β_{KM}	-0.0190	-20.33[a)]	-0.0186	-20.49[a)]	-0.0189	-19.89[a)]
Ln(K)* Ln(E)	β_{KE}	-0.0014	-1.48[c)]	-0.0017	-1.79[b)]	-0.0014	-1.47[c)]
$[Ln(M)]^2$	β_{MM}	0.0698	87.15[a)]	0.0701	88.42[a)]	0.0704	86.25[a)]
Ln(M)* Ln(E)	β_{ME}	-0.0638	-52.29[a)]	-0.0641	-52.94[a)]	-0.0641	-52.01[a)]
$[Ln(E)]^2$	β_{EE}	0.0327	42.78[a)]	0.0328	43.65[a)]	0.0330	42.64[a)]
Ln(L)*T	β_{LT}	0.0047	2.35[a)]	0.0047	2.35[a)]	0.0045	2.28[b)]
Ln(K)*T	β_{KT}	-0.0003	-0.36	-0.0001	-0.17	-0.0005	-0.59
Ln(M)*T	β_{MT}	-0.0036	-3.39[a)]	-0.0033	-3.11[a)]	-0.0035	-3.24[a)]
Ln(E)*T	β_{ET}	0.0022	2.07[b)]	0.0017	1.59[c)]	0.0022	2.03[b)]
T^2	β_{TT}	-0.0035	-3.38[a)]	-0.0037	-3.62[a)]	-0.0036	-3.51[a)]

Variables	Parameters	Model 1		Model 2		Model 3	
		Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
Inefficiency function (dep var: u)							
Constant	δ_0	-0.2257	-12.47 a)	-0.3752	-13.31 a)	-0.1753	-10.68 a)
LQ (specialization)	δ_1	-0.1477	-19.66 a)	-0.0726	-6.53 a)	-0.1101	-21.82 a)
DIV (diversity)	δ_2	0.0677	27.11 a)	0.0565	15.57 a)	0.0571	27.01 a)
COM (competition)	δ_3	(-)		0.1651	10.49 a)	0.0278	2.62 a)
Age (firm age)	δ_4	(-)		(-)		-0.0006	-8.94 a)
SIZE (firm size)	δ_5	(-)		(-)		-0.0132	-9.27 a)
CR4 (concentration ratio)	δ_6	(-)		(-)		0.1201	8.47 a)
DURB (dummy urban)	δ_7	-0.2516	-20.44 a)	-0.2602	-23.07 a)	-0.2743	-21.90 a)
DLOC (dummy location)	δ_8	-0.0357	-3.38 a)	-0.0394	-4.33 a)	-0.0184	-2.74 a)
	σ^2	0.1466	106.23 a)	0.1464	106.33 a)	0.1465	106.45 a)
	γ	0.0238	15.78 a)	0.0183	8.40 a)	0.0184	9.40 a)
Mean of TE		0.9084		0.9138		0.9156	
Establishments		4,240		4,240		4,240	
Observations		25,440		25,440		25,440	

Note: a), b), and c) denote 1%, 5%, and 10% significance level, respectively.

To see the actual influence of the factor inputs upon the output level in the production process, we need to calculate the elasticities for each production input. Table 5.6 shows the output elasticities with respect to labour, capital, materials, and energy during the period 2004–2009. All the elasticities are positive; of these, the elasticity for materials, with an average of 0.396, is the highest. This is not surprising, because raw materials represent the largest share in the structure of production inputs. In 2009, for example, the expenditure for raw materials in the structure of production inputs is 77.6 percent. The percentage value for this expenditure is similar from year to year. Related to this issue, Aswicahyono et al. (1996) and Dhanani (2000) argue that Indonesian manufacturing products are dominated by resource-based or simple assembly-processed products which causes the industry to rely heavily on raw materials.

On the other hand, the output elasticity for capital is relatively small, 0.166. This is also as expected, as Indonesian manufacturing is generally dominated by light or labour intensive industries, which do not depend much on capital. As argued by Hill (1990a, 1990b), capital intensive industries are mostly related to heavy-processing industries such as chemical and chemical products or heavy-engineering industries such as machines and transport equipment.

Table 5.6: Elasticities of Output with respect to Production Inputs, 2004–2009[10]

Year	L	K	M	E	RTS
2004	0.294	0.163	0.401	0.215	1.072
2005	0.313	0.176	0.379	0.216	1.084
2006	0.290	0.138	0.425	0.211	1.064
2007	0.293	0.144	0.411	0.222	1.070
2008	0.304	0.153	0.407	0.213	1.077
2009	0.342	0.223	0.353	0.199	1.117
Average	0.306	0.166	0.396	0.212	1.081

Source: Author's calculation.

[10] The output elasticity of each production input is calculated by taking a partial derivative of the production *translog* model. Based on Equation (5.1), the output elasticity of labour is defined as $\varepsilon_L = \beta_L + 2\beta_{LL}(lnL) + \beta_{LK}(lnK) + \beta_{LM}(lnM) + \beta_{LE}(lnE) + \beta_{LT}(T)$. The same procedure is used to calculate the output elasticity with respect to capital, materials and energy.

Moving to the return to scale (RTS), Table 5.6 presents the scores of return to scale in manufacturing industries from 2004 to 2009. The RTS is the sum of output elasticities with respect to all production inputs. The average score is 1.081, greater than 1, implying that in the period 2004 to 2009 manufacturing industries in Indonesia experienced increasing returns to scale (IRTS). The result of increasing returns to scale is consistent with the rejection of the first hypothesis, the Cobb-Douglas production function, which assumes constant returns to scale (CRTS) in its technological set.

In addition, the average score of technical efficiency (TE) in Indonesian manufacturing industries from 2004 to 2009 increases consistently, with an average around 91.56 percent. This TE score is relatively higher than those of previous findings in Indonesia. Margono and Sharma (2006) find the average technical efficiency 55.9 percent for four industrial sectors: food, textiles, chemical and metal products during the period 1993 to 2000. However, in particular industrial sectors such as metal products, the technical efficiency is as high as to 85.8 percent in 2000. Similarly, Hill and Kalirajan (1993) find the average technical efficiency to be 62.5 percent for the small garments industry for the year 1986, while Pitt and Lee (1981) report an average of 67.7 percent technical efficiency for the weaving industry in period 1972 to 1975.

The rejection of the no-technological progress hypothesis is noted above. In model 3, the coefficient for time (T) is positive (0.0347) and significant at 1 percent, suggesting that, in general, technological progress occurs over time. The output level increases 3.08 percent per annum during 2004 to 2009, due to technical progress. The finding of annual technological progress is in line with previous studies, such as those of Margono and Sharma (2006). They find technical progress of 10.54 percent per annum in food industries for the period 1993 to 2000. Ikhsan (2007) reports that technological progress occurred at 7.16 percent for period 1988–1992 and 5.45 percent per annum for the period 1993–1996 in across all manufacturing industries. Meanwhile, Suyanto et al. (2009) note that domestic firms have technological progress of 0.5 percent per year during the period 1988 to 2000. In addition, the value of γ is relatively small (0.0184), reflecting the high score of technical efficiency and the small effect of inefficiency to the firm output as presented in Table 5.5.

5.5.3. Agglomeration Economies and Firm Location

The effect of agglomeration economies and firm characteristics on firm-level technical efficiency is represented by the estimation results of the inefficiency function in Table 5.5.

5.5.3.1. Agglomeration Economies

The estimation result shows that the coefficient of specialization (or MAR externalities) is negative and significant at 1 percent. This indicates that regions with higher industrial specialization or a high relative level of regional specialization promote higher firm-level technical efficiency. Thus, in the period 2004 to 2009 the more specialized the industries in a particular region relative to the specialization of industries in all regions, the greater that region' firm-level technical efficiency. It also suggests that a high share of a particular or dominant industry in a region will stimulate higher firm-level technical efficiency in that entire region. The positive effect of industrial specialization upon firm-level technical efficiency ultimately lifts the firm productivity, as technical efficiency is component of the total factor productivity (TFP).

This finding supports the previous studies in Indonesia, such as that of Kuncoro (2009). He analyses the impact of specialization and diversity upon labour productivity in several industries by comparing three different periods: 1990–1995, 1997–2000, and 2001–2003. This results show that in general the magnitude of the influence of specialization is greater than that of diversity, especially in the textiles, garments, leather, footwear, chemicals and machineries industries. The nature of externalities and agglomeration favour industrial spillovers, that is, localization is seen to be stronger than urbanization effects. Other evidence of agglomeration economies in Indonesia have been noted by Deichmann et al. (2005), who claim that the level of industrial and geographical aggregation has a considerable impact on location decisions of firms in a majority of industries.

The estimation result shows the important role of industrial specialization on stimulating firm technical efficiency. To get broader perspective, Table 5.7 highlights industrial specialization by provinces at the 2-digit ISIC level. As manufacturing industries are highly concentrated in Java, the provinces in this region dominate the number of specialized industries except for Central Java, in which this province only has six specialized industries of the 23 sub-sectors established.

Table 5.7: Industrial Specialization at 2-digit ISIC by Region 2009[11]

	Provinces	ISIC																							
		15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	T (+)
11	Aceh	+		-	-		-		-		+		+									-	-		3
12	North Sumatera	+	-	-	-	-	+	-	+	+	-	+	-	+	-	-		-	-	+	-	-	-	+	8
13	West Sumatera	+		-	-	-	-	-	+	+	-	+	+		-						-	-	-		5
14	Riau	+	-	-			+	+	+	-	-	-	-									-	-		4
15	Jambi	+		-			+	+	-		-	+	-									-	-		4
16	South Sumatera	+		-	-		+	-	-	+	+	+	-	-	-					-	-	-	-		5
17	Bengkulu	+			-				+			+	-		-								-		3
18	Lampung	+	-	-	-		+	-	-	+	+	-	-	-	-	-					-	-	-		4
19	Babel	+							+	+		-	+	+								-			5
21	Riau Islands	-	-	-	-	-	-	-	-		-	-	-	+	+	+	+	+	+	+	-	+	-	-	8
31	Jakarta	-		-	+	-	-	-	+	-	+	-	-	+	+	+	-	+	-	-	+	+	-	+	10
32	West Java	-	-	+	+	-	-	-	-	-	-	-	+	-	+	+	+	+	+	+	+	+	-	-	11
33	Central Java	-	+	+	+	-	+	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-	6
34	Yogyakarta	-	+	+	+	-	-	-	+	+	-	-	+		-	+		-		+	-	-	+	+	10
35	East Java	+	+	-	-	-	+	+	-	+	-	+	+	-	+	-	-	-	-	-	-	-	+	+	10
36	Banten	-		-	-	+	-	+	-	+	+	+	+	+	+	+		+	-	-	-	+	-	+	12
51	Bali	+		-	+	-	+	-	+	-	-	-	+		-							-	+	+	7
52	NTB	+	+	-	-		+		+				+									-	-	+	6
53	NTT	+		+	-		-		+		+		+										+		6
61	West Kalimantan	+			-		+	-	-	+	-	+	-	-	-								-	-	4
62	Central	+					+	-	-	+		-	-			-							-		3

[11] The specialization level is calculated by the difference of $s_{ij}^{C} - s_{*j}$ where s_{ij}^{C} reflects the employment share of industry i, region j, of total (national) industry i employment and s_{*j} reflects the relative size of economic activity in terms of each region's total employment share. The (+) sign indicates that region j is more specialized in industry i compared to industries overall, or the employment share of industry i in region j is high relative to the share of total employment in region j (Nakamura and Paul 2009).

	Provinces	ISIC																							
		15	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**T (+)**
	Kalimantan																								
63	South Kalimantan	+		-	-		+		+		-	+	-		-						-	-	-		4
64	East Kalimantan	+		-	-	-	+		-	+	+	-	-	-	-	-						+	-		5
71	North Sulawesi	+		-			-		+	+	-	-	-	-	-							+	-		4
72	Central Sulawesi	+	-				+		+				+										+		5
73	South Sulawesi	+	-	-	-	-	+	-	-		-	-	+	-			-	-			-	-	-		3
74	Southeast Sulawesi	+		-			+		+	+		-	+	+	+							-	-		7
75	Gorontalo	+		-			-			+			-		-								-		2
76	West Sulawesi	+		-			-				-												-		1
81	Maluku	+					+		+		-	+										+	-		5
82	North Maluku						+		+													+	+		4
91	West Irian	+					+		+	+			-									+			5
94	Papua	+				+			+				-										-		3
	Total (+)	26	4	4	5	2	19	4	19	15	7	10	13	6	6	5	2	4	2	4	2	9	7	7	

Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

From a sectoral perspective, food and beverages industry (ISIC 15) is found to be the most popular sector, being specialized in 26 provinces. This is followed by wood and wood products' industry (ISIC 20) and publishing and printing industry (ISIC 22), both of which industries are specialized in 19 provinces.

Moving to the effect of diversity (or Jacobs' externalities) upon firm-level technical efficiency, the estimation result shows a positive relation between diversity and firm-level technical inefficiency. This indicates that a high level of diversity in a region tends to reduce firm-level technical efficiency that is firms located in highly diversified regions tend to have lower technical efficiency levels. In the Indonesian case, this finding is consistent with Kuncoro (2009), who finds that greater diversity led to lower levels of productivity in several manufacturing industries for the period 1990 to 2003.

The estimation results above indicate that in the period 2004 to 2009 specialization (or MAR externalities), is more conducive to stimulating firm-level technical efficiency than Jacobs' externalities (diversity). This fact confirms that knowledge spillovers are more prevalent in firms of the same industry than in firms of different industries. Furthermore, if firms in the same industry are located close to firms of their industry, they will benefit from the emergence of knowledge, network and technology spillovers (Henderson 2003; Koo 2005).

The relative importance of specialization to a firm's technical efficiency found in this study is in accordance with the empirical results in various international cases, for example: Nakamura (1985) finds that localization economies positively impact productivity in Japanese manufacturing industries; similarly Henderson (1986) for numerous industries in the U.S. and Brazil manufacturing industries. Each of those studies is more favourable to the existence of localization economies than urbanization economies. Duranton and Puga (2001) obtain a similar result using French data. Henderson et al. (2001) find similar result in selected Korean manufacturing industries from 1983 to 1993, where MAR externalities positively affect productivity. Adopting a different approach, Lee et al. (2010) find the same positive impact using the data of the Korean Mining and Manufacturing Survey (MMS) in 2000. In another case, Henderson (1997) finds that both MAR externalities and Jacobs' externalities matter for the capital goods industries. He argues that cities or regions are highly specialized in manufacturing activities, reflecting the benefits of concentration. However, having a diversified employment base can also be important for a metropolitan area.

The third agglomeration economies variable in the technical inefficiency function is competition (or Porter's externalities). Similar to that for diversity, the coefficient for competition is positive. With regard to the definition of competition used in this study, the estimation results indicate that the regions with high level of competition, or the regions dominated by small firms, tend to be more conducive to fostering firm-level technical efficiency. The results also mean that firms located in the competitive regions tend to experience higher technical efficiency than firms located in more oligopolistic or monopolistic regions.

This shows that local competition plays crucial role in the transmission of knowledge spillovers among firms in a particular region. Moreover, this finding clearly supports Porter's argument for the importance of competition for stimulating firm productivity, a position that is consistent with Jacobs'. Porter concurs with Jacobs about the role of local competition in the transmission of knowledge across industries, but regarding intra-industries knowledge spillovers, he agrees with the MAR hypothesis. To illustrate the nature of competition in Indonesia, Table 5.8 presents the market environment at the regional level, which is specified and measured by province.

Based on Table 5.8, the competitive provinces are considered the regions that are more conducive in stimulating firm-level technical efficiency than those regions that have oligopolistic or monopolistic market structure. These competitive regions are dominated by small- and medium-scale industries. However, in fact, most provinces' market structures are close to being monopolistic or oligopolistic. These conditions show that the contribution of large-scale firms to the manufacturing industry as a whole is still dominant, although the competitive regions are actually better for supporting firm-level technical efficiency than oligopolistic or monopolistic regions.

Table 5.8: Location Quotient and Regional Industrial Environment 2009

	Region/Province	LQ_{ij}^{L}	LQ_{ij}^{F}	LQ_{ij}^{L}/LQ_{ij}^{F}	Regional Environment
11	Aceh	0.485	0.507	0.955	Competitive
12	North Sumatera	0.993	0.807	1.231	Monopolistic/oligopolistic
13	West Sumatera	0.651	0.567	1.148	Monopolistic/oligopolistic
14	Riau	0.744	0.535	1.391	Monopolistic/oligopolistic
15	Jambi	0.596	0.595	1.002	Monopolistic/oligopolistic
16	South Sumatera	0.731	0.842	0.868	Competitive
17	Bengkulu	0.537	0.508	1.057	Monopolistic/oligopolistic
18	Lampung	0.518	0.610	0.850	Competitive
19	Babel	2.209	1.739	1.270	Monopolistic/oligopolistic
21	Riau Islands	1.806	3.415	0.529	Competitive
31	Jakarta	1.260	1.259	1.001	Monopolistic/oligopolistic
32	West Java	1.126	1.065	1.057	Monopolistic/oligopolistic
33	Central Java	0.711	0.736	0.966	Competitive
34	Yogyakarta	1.003	1.063	0.943	Competitive
35	East Java	0.886	0.953	0.930	Competitive
36	Banten	1.137	1.384	0.822	Competitive
51	Bali	0.718	0.650	1.105	Monopolistic/oligopolistic
52	NTB	0.957	0.778	1.230	Monopolistic/oligopolistic
53	NTT	0.922	0.535	1.722	Monopolistic/oligopolistic
61	West Kalimantan	1.009	1.022	0.988	Competitive
62	Central Kalimantan	0.554	0.829	0.668	Competitive
63	South Kalimantan	0.616	0.733	0.840	Competitive
64	East Kalimantan	0.966	1.018	0.949	Competitive
71	North Sulawesi	0.922	0.784	1.177	Monopolistic/oligopolistic
72	Central Sulawesi	0.675	0.583	1.158	Monopolistic/oligopolistic
73	South Sulawesi	0.638	0.567	1.124	Monopolistic/oligopolistic
74	Southeast Sulawesi	1.649	0.813	2.029	Monopolistic/oligopolistic
75	Gorontalo	1.373	0.888	1.546	Monopolistic/oligopolistic
76	West Sulawesi	0.294	0.416	0.707	Competitive
81	Maluku	0.638	0.893	0.715	Competitive
82	North Maluku	1.364	1.526	0.894	Competitive
91	West Irian	0.905	1.503	0.602	Competitive
94	Papua	0.601	0.586	1.026	Monopolistic/oligopolistic

Note: LQ_{ij}^{L} is labour-based LQ; LQ_{ij}^{F} is firms-based LQ. Regional monopolistic/oligopolistic environment indicates that region j contains relatively large plants while regional competitive environment indicates that region j contains relatively small plants (Nakamura and Paul 2009).

Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

5.5.3.2. Urban Area and Industrial Complex

Firm location such as urban region and industrial complex are considered as the important factors that affect firm-level technical efficiency. Urban region is associated with regions that have adequate and good public infrastructure and business facilities. By its nature, this will attract firms to locate in the region. Urban areas are generally formed through a natural process that follows the development policies adopted by the government. On the other hand, industrial complex tends to be created by special policies implemented by the government in order to accelerate the performance of particular industries.

The estimation result for the dummy variable of urban area is negative and significant at 1% level, implying that firms located in urban areas tend to be more technically efficient than firms located in non-urban areas. This result confirms that urban area is important for stimulating firm-level technical efficiency and productivity. This finding is not surprising, due to the above mentioned fact that urban areas can provide better public facilities and infrastructures. In Indonesia many urban regions are located adjacent to each other, as existing groups' and these groups normally have good access to centres of growth.

Theoretically, urban areas may be advantageous for industrial agglomeration in terms of regional advantages, home market effect and consumption levels. Home market effect implies that locations with larger local demand attract a more than proportionate share of firms in imperfectly competitive industries (Ottaviano and Thisse 2004). Moreover, in some aspects urban areas are like cities. Glaeser et al. (2001) mention that cities can provide benefits to firms in ways, such as increased consumption levels through the availability of goods and services, the availability of public goods, and more interaction between firms in the same industry due to the level of density and offer various other economic opportunities.

Referring to Table 2.7 (in Chapter 2), Table 5.9 shows the distribution of manufacturing industries in selected urban areas for value added, labour and number of firms.

Table 5.9: Spatial Distribution of Manufacturing Industries 2009

No	Group of Regions	Value Added (trillion IDR)	Labour (000)	Firm	Share to national level (%)		
					VA	Labour	Firm
1	**Jakarta and Surrounds**	**384.5**	**1358.1**	**5324**	**48.0**	**31.3**	**21.8**
	Jakarta	110.9	311.9	1635	13.9	7.2	6.7
	Serang	16.3	63.8	144	2.0	1.5	0.6
	Tanggerang (regency and city)	48.5	385.8	1433	6.1	8.9	5.9
	Bogor (regency and city)	91.9	179.4	765	11.5	4.1	3.1
	Bekasi (regency and city)	66.5	262.2	891	8.3	6.0	3.6
	Karawang	31.5	106.6	288	3.9	2.5	1.2
	Depok (city)	4.4	27.6	96	0.6	0.6	0.4
	Cilegon	14.5	20.8	72	1.8	0.5	0.3
2	**Surabaya and Surrounds**	**98.9**	**654.7**	**3858**	**12.4**	**15.1**	**15.8**
	Surabaya (city)	22.1	140.4	845	2.8	3.2	3.5
	Gresik	13.6	97.2	494	1.7	2.2	2.0
	Sidoardjo	25.1	161.2	853	3.1	3.7	3.5
	Malang (regency and city)	10.7	85.5	455	1.3	2.0	1.9
	Pasuruan	14.4	101.4	698	1.8	2.3	2.9
	Probolinggo(regency and city)	1.7	18.8	104	0.2	0.4	0.4
	Mojokerto (regency and city)	6.5	42.0	273	0.8	1.0	1.1
	Tuban	4.9	8.2	136	0.6	0.2	0.6
3	**Kediri (regency and city)**	**27.2**	**54.8**	**152**	**3.4**	**1.3**	**0.6**
4	**Bandung and Surrounds**	**29.8**	**372.4**	**1977**	**3.7**	**8.6**	**8.1**
	Bandung (regency and city)	13.4	234.5	1599	1.7	5.4	6.5
	Purwakarta	6.8	46.2	159	0.9	1.1	0.6
	Cimahi	7.0	70.8	136	0.9	1.6	0.6
	Sumedang	2.6	20.8	83	0.3	0.5	0.3
5	**Riau**	**23.7**	**23.3**	**40**	**3.0**	**0.5**	**0.2**
	Pelelawan	9.9	6.5	17	1.2	0.2	0.1
	Dumai	6.1	1.6	7	0.8	0.0	0.0
	Siak	5.1	12.2	16	0.6	0.3	0.1
	Indragiri Hilir	2.6	2.9	15	0.3	0.1	0.1
6	**East Coast Sumatra**	**20.3**	**103.5**	**747**	**2.5**	**2.4**	**3.1**
	Asahan	0.9	6.4	123	0.1	0.1	0.5
	Medan	10.0	36.1	166	1.2	0.8	0.7
	Labuhan Batu	0.6	3.7	20	0.1	0.1	0.1
	Deli Serdang	3.5	47.7	350	0.4	1.1	1.4
	Tapanuli Selatan	0.1	0.3	2	0.0	0.0	0.0
	Batu Bara	3.5	5.0	48	0.4	0.1	0.2
	Pematang Siantar	1.7	4.3	38	0.2	0.1	0.2
7	**Palembang & surrounds**	**22.3**	**30.6**	**148**	**2.8**	**0.7**	**0.6**
	Palembang (city)	8.0	16.2	96	1.0	0.4	0.4
	Banyu Asin	3.9	11.5	37	0.5	0.3	0.2
	Ogan Ilir	10.5	2.9	24	1.31	0.07	0.10

No	Group of Regions	Value Added (trillion IDR)	Labour (000)	Firm	Share to national level (%)		
					VA	Labour	Firm
8	**Semarang and Surrounds**	**25.8**	**341.1**	**1484**	**3.2**	**7.9**	**6.1**
	Semarang (regency and city)	9.8	152.9	472	1.2	3.5	1.9
	Kendal	2.4	17.8	46	0.3	0.4	0.2
	Salatiga (city)	0.6	7.6	23	0.1	0.2	0.1
	Kudus	10.3	96.6	179	1.3	2.2	0.7
	Demak	1.2	12.9	59	0.2	0.3	0.2
	Pekalongan (regency & city)	0.9	39.0	595	0.1	0.9	2.4
	Magelang (regency & city)	0.6	14.4	110	0.1	0.3	0.4
9	**Batam and surrounds**	**23.7**	**141.9**	**326**	**3.0**	**3.3**	**1.3**
	Batam	21.8	130.0	287	2.7	3.0	1.2
	Bintan	1.9	11.9	39	0.2	0.3	0.2
10	**Surakarta and surrounds**	**9.2**	**141.3**	**895**	**1.2**	**3.3**	**3.7**
	Surakarta (city)	0.6	14.8	184	0.1	0.3	0.8
	Sukoharjo	4.1	47.1	145	0.5	1.1	0.6
	Karanganyar	2.5	45.1	155	0.3	1.0	0.6
	Sragen	1.5	14.5	57	0.2	0.3	0.2
	Klaten	0.5	19.9	354	0.1	0.5	1.4
11	**Samarinda & surrounds**	**6.6**	**19.6**	**76**	**0.8**	**0.5**	**0.3**
	Samarinda	0.4	3.9	30	0.1	0.1	0.1
	Balikpapan	1.7	8.3	28	0.2	0.2	0.1
	Bontang	3.3	3.5	8	0.4	0.1	0.0
	Kutai	1.2	3.9	10	0.2	0.1	0.0
12	**Padang**	**5.7**	**6.9**	**54**	**0.7**	**0.2**	**0.2**
13	**Pangkal Pinang**	**3.0**	**5.2**	**21**	**0.4**	**0.1**	**0.1**
	Total of groups	**680.8**	**3253.3**	**15102**	**85.06**	**74.87**	**61.72**

Source: Large and Medium Industrial Statistics 1976-2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

In Table 5.9, it is clear that urban regions contribute high share of value-added (85.06 percent), labour (74.84 percent), and number of firms (61.72 percent) to manufacturing industries as a whole. This feature supports the premise that firms located in these areas are likely to have higher technical efficiency.

Furthermore, the second dummy variable represents an industrial complex or industrial area. The estimation result for this variable is negative, in line with the result for urban area. This indicates that firms located inside an industrial complex tend to have higher technical efficiency than firms located outside an industrial complex. This finding is as expected because industrial complexes normally provide a sound environment for firms to carry out their production processes. The emergence of industrial areas in Indonesia began with Presidential Decree 41/1996. The decree is strengthened by a more comprehensive formal regulation namely the Government Regulation no 24/2009, which is issued after a period of rapid growth in industrial areas in Indonesia. The establishment of industrial areas is mostly initiated by the private sector, in which the government take a position as regulator and facilitator. The nature of industrial areas in Indonesia cannot be directly compared to with that of industrial complexes or districts in developed countries, for example Silicon Valley in U.S and Emilia Romagna in Italy. However, the spirit is the same: to increase the performance of firms by providing better infrastructure and a sound business environment.

Table 5.10 shows the proportion of firms located inside or outside industrial areas in 2009. Only 6.71 percent or 1,641 firms are located inside industrial complexes, while 93.29 percent or 22,287 firms are located outside these industrial areas. From a total of 23 industrial sectors, only four industry sub-sectors have a relatively high share of firms located inside industrial areas i.e. basic metals–ISIC 27 (23.5%), electrical machinery–ISIC 31 (20.56%), radio, TV and communication apparatus–ISIC 32 (35.19%) and medical and optical instruments–ISIC 33 (29.85%). The advantages of a firm being located inside an industrial area are that the flows of experience, information and knowledge within the area are more effective, as there is less constraint to these interchanges (Marshall 1920). Further, forms benefit from collective competencies (Storper 1995) and collective learning (Cappelo 2002).

Table 5.10: Number of Firms Located in Industrial Area/Complex 2009

ISIC	Industries	Number of firms			(%)	
		inside	outside	Total	inside	outside
15	Food products and beverages	316	5555	5871	5.38	94.62
16	Tobacco	53	998	1051	5.04	94.96
17	Textiles	100	2501	2601	3.84	96.16
18	Wearing apparel	30	2110	2140	1.40	98.60
19	Tanning and dressing of leather	49	620	669	7.32	92.68
20	Wood and products of wood except furniture and plating materials	64	1188	1252	5.11	94.89
21	Paper and paper products	19	433	452	4.20	95.80
22	Publishing, printing and reproduction of recorded media	17	678	695	2.45	97.55
23	Coal, refined petroleum products and nuclear fuel	7	66	73	9.59	90.41
24	Chemicals and chemical products	126	963	1089	11.57	88.43
25	Rubber and plastics products	220	1419	1639	13.42	86.58
26	Other non-metallic mineral products	38	1660	1698	2.24	97.76
27	Basic metals	55	179	234	23.50	76.50
28	Fabricated metal products, except machinery and equipment	93	820	913	10.19	89.81
29	Machinery and equipment n.e.c	52	357	409	12.71	87.29
30	Office, accounting, and computing machinery	1	8	9	11.11	88.89
31	Electrical machinery and apparatus n.e.c	51	197	248	20.56	79.44
32	Radio, television and communication equipment and apparatus	76	140	216	35.19	64.81
33	Medical, precision and optical instruments, watches and clocks	20	47	67	29.85	70.15
34	Motor vehicles, trailers and semi-trailers	21	262	283	7.42	92.58
35	Other transport equipment	47	277	324	14.51	85.49
36	Furniture and manufacturing n.e.c	177	2232	2409	7.35	92.65
37	Recycling	9	117	126	7.14	92.86
	Total	1,641	22,827	24,468	6.71	93.29

Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

5.5.4. Firm Characteristics and Technical Efficiency

As well as the variables of agglomeration economies or dynamic externalities, this study includes other variables considered to be determinants of firm-level technical efficiency, i.e. firm age (AGE), firm size (SIZE), and concentration ratio (CR4). As characteristics of the firm, these variables also represent firm structure and conduct. The following sub-section discusses the estimation results for these related variables.

5.5.4.1 Firm Age (AGE)

In Table 5.5, the estimation result of firm age (AGE) shows a negative effect upon firms-level technical inefficiency. This indicates that older firms have higher levels of technical efficiency than younger firms. The suggested reason for this finding is that older firms have more experience in handling equipment and surviving in difficult economic conditions than do younger firms. Therefore, older firms are likely to carry out their production processes and management more efficiently than younger ones (Arrow 1962). Thus, the older firm benefits from its accumulated experience in production. As a consequence, they are technically more efficient. This shows the presence of 'learning-by-doing' (Wu 1994).

This result concurs with that of previous studies; for example, Chen and Tang (1987) argue that the firm's experience is central to older firms being more technically efficient than younger firms. More recent studies, such as that by Brouwer et al. (2005), divide firm age into various categories and their results show the older group of firms are technically more efficient in their production processes. Firm productivity increases with age. Lee et al. (2010) also find a similar result when they analyse Marshall's scale economies and Jacobs' externalities in Korean manufacturing industries. Again, older firms tend to have higher productivity. Similar results are found in: Wu (1994) in Chinese rural textiles firms; Battese and Coelli (1995) for the agricultural sector in Australia, where older farmers are more technically efficient; Henderson (1986) in Brazilian manufacturing industries; and Kalkulis (2010) in semi-conductor and pharmaceutical industries in the U.S. However, for the Indonesian case, the results conflict with the results of Pitt and Lee (1983), Hill and Kalirajan (1993) and Suyanto et al. (2009), who find that firm age has a negative effect upon firm-level technical efficiency. This is possible due to the different periods used in these three studies and the characteristics of firms they examined.

5.5.4.2. Firm Size (SIZE)

The second variable is firm size (SIZE). Its coefficient is also negative, which implies that larger firms tend to have higher technical efficiency levels than the smaller firms. It also indicates that large firms in Indonesian manufacturing industries can effectively manage their power to control the market so that they can reach an optimal level of technical efficiency and place the small firms or new entrants in the position of 'followers'.

This finding is similar to those of the previous research; for example, Pitt and Lee (1981) find that firm size positively effects the technical efficiency level in the

Indonesian weaving industry; Bhandari and Ray (2012) find similarly for the Indian textile industry; Fan and Scott (2003) report likewise for furniture and plastic products in Chinese industries; Cingano and Schivardi (2004) for Italian manufacturing industries; Kalkulis (2010) for the semi-conductor and pharmaceutical industries in the U.S; and, finally, Jennen and Verwijmeren (2010) find a similar result in Dutch firms, where size positively impacts firms' financial performance.

One area related to firm size is market share: larger firms generally tend to have larger market shares. The results in this study are also consistent with those of previous studies using market share as an indicator of size– for instance, Prabowo and Cabanda (2011), who analysed manufacturing companies listed on the Indonesian Stock Exchange from 2000 to 2005. The finding also supports those of Tybout (2000) for various industries in developing countries and Diaz and Sanchez (2008) for small-medium manufacturing industries in Spain from 1995 to 2001. It is also similar to the finding from Banker et al. (2010), who examine the positive impact of market share upon productivity improvement and technological progress in the U.S. mobile telecommunications industry.

5.5.4.3. Industrial Concentration (CR4)

The third variable is industrial concentration (CR4). The estimation results show a positive sign for this variable, indicating that firms in a competitive business environment will tend to have higher technical efficiency levels than firms in a less competitive market. It also means that an oligopolistic or monopolistic industrial structure is not suitable for driving firm-level technical efficiency. This result is in line with Setiawan et al. (2012). They find a positive relation between industrial concentration and inefficiency-level in Indonesian food and beverages industries at the 5-digit ISIC level for the periods of 1995 to 2006. Competition is important because equal power between firms in an industry will reduce levels of market inefficiency. By its nature, competition will stimulate firms to achieve their optimal level of technical efficiency.

To investigate the actual market condition for Indonesian manufacturing industries, Table 5.11 shows the industrial concentration ratio for two-digit ISIC level. From the above table, it appears that the majority of industries have an oligopolistic structure.

Table 5.11: Concentration Ratio (CR4) in 2-Digit ISIC 2009

ISIC	Industries	CR4
15	Food products and beverages	16.42
16	Tobacco	59.63
17	Textiles	33.59
18	Wearing apparel	28.02
19	Tanning and dressing of leather	48.01
20	Wood and products of wood except furniture and plating materials	12.91
21	Paper and paper products	56.03
22	Publishing, printing and reproduction of recorded media	23.54
23	Coal, refined petroleum products and nuclear fuel	61.38
24	Chemicals and chemical products	52.81
25	Rubber and plastics products	17.70
26	Other non-metallic mineral products	45.38
27	Basic metals	37.12
28	Fabricated metal products, except machinery and equipment	29.46
29	Machinery and equipment n.e.c	45.01
30	Office, accounting, and computing machinery	96.75
31	Electrical machinery and apparatus n.e.c	38.89
32	Radio, television and communication equipment and apparatus	32.76
33	Medical, precision and optical instruments, watches and clocks	66.76
34	Motor vehicles, trailers and semi-trailers	60.16
35	Other transport equipment	74.82
36	Furniture and manufacturing n.e.c	24.35
37	Recycling	23.50
	Average	42.83

Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

In 2009, for example, the industrial concentration ratios (CR4) for 11 industries in 2-digit ISIC were greater than 40 percent, with the average for all 23 industries being 42.82 percent. With regard to the estimation results, the market concentration in Table 5.11 is actually not conducive to stimulating firm-level technical efficiency. Thus, as mentioned, the oligopolistic and monopolistic structure of Indonesian industries has been widely concerned since the early 1990s, because it is considered as one of the main determinants of market distortion.

5.6. Conclusion

The focus of this chapter is to estimate the impact of agglomeration economies upon firm-level technical efficiency using the flexible translog production frontier. The estimation results for the main production inputs are consistent with the theory, where labour, capital, material, and energy positively impact the firm output level. In general, during the period 2004–2009 manufacturing industries in Indonesia experienced technical progress. This is represented by the positive coefficient of time (T). Meanwhile, the findings for agglomeration economies suggest that specialization (or MAR externalities) is more conducive for firm-level technical efficiency than Jacobs' externalities, implying that knowledge spillovers are more effectively transferred among firms in the same industry than diverse industries. Moreover, the results show that local competition (or Porter's externalities) is better for stimulating firm-level technical efficiency than oligopolistic/monopolistic. The findings also confirm that urban areas and industrial complexes contribute positive effects, meaning that a sound business environment and adequate infrastructures are necessary conditions needed to improve firm-level technical efficiency.

In terms of firm characteristics, there are several different interpretations. The sign of firm age indicates that older firms tend to have higher technical efficiency than younger firms, as they have longer experience– not only in managing their firms but also in facing external shocks. The higher technical efficiency of larger firms implies that firm size has a positive association with firm-level technical efficiency. For the market structure, the results show that a competitive market stimulates greater firm-level technical efficiency than an oligopolistic or monopolistic market, which is indicated by the positive coefficient of the concentration ratio.

From industrial policy perspective, the estimation results indicate that the Indonesian government, especially in formulating national industrial policy, should consider the existence of industrial agglomeration. Industrial agglomeration in Indonesia is confirmed as having positive impact upon the firm-level technical efficiency and it may have an important role in increasing productivity in the long-term. This finding is supported by the fact that manufacturing industries in Indonesia tend to be concentrated around centres of growth. Moreover, from a macroeconomic point of view, improved productivity levels can potentially increase earnings, income and standards of living. The level of a country's productivity is proportional to its people's standard of living, meaning that higher productivity contributes to a higher standard of living. Furthermore, as the presence of industrial complexes has a positive effect upon firm technical efficiency, the government should continue to implement this policy by creating the number of industrial complexes needed to promote a better business environment for the firms.

Although the estimation results clearly show that MAR externalities positively impact firm-level technical efficiency, this does not directly represent the impact of agglomeration externalities upon total factor productivity (TFP) growth, as technical efficiency is only one component of its. Conceptually, TFP growth can be decomposed into at least three components, i.e. technical change, scale and technical efficiency change (Khumbakar and Lovell 2000; Coelli et al. 2005). However, O'Donnell (2012) proposes an even more comprehensive decomposition of TFP growth. In the literature, the decomposition of TFP growth can be performed by various methods, such as stochastic frontier analysis (SFA), data envelopment analysis (DEA), and index measurements. Apropos this, the next chapter will discuss and analyse the decomposition of total factor productivity (TFP) growth in Indonesian manufacturing industries. This discussion will detail the sources that contribute to TFP growth in Indonesian manufacturing industries.

Chapter 6

The Decomposition of Total Factor Productivity (TFP) Growth

6.1. Introduction

Chapter 5 discusses the effects of agglomeration economies and dynamic externalities upon firm-level technical efficiency, which is estimated using the stochastic production frontier (SPF). In the production function, technical efficiency represents a movement in the production process toward the frontier without requiring extra input. This movement can be stimulated by various factors, such as the accumulation of knowledge in the learning-by-doing process, the diffusion of new technology, improved managerial practice and so on (Coelli et al. 2005). Technical efficiency is one of sources of total factor productivity (TFP) growth, in which TFP growth can be decomposed into at least four change components, namely technical, scale efficiency, technical efficiency and allocative efficiency (Kumbhakar and Lovell 2000; Coelli et al. 2005).

To continue the discussion of the previous chapter, this chapter analyses the decomposition of TFP growth in Indonesian manufacturing industries during the period of 2000 to 2009. This period is crucial because after the economic crisis in 1998 the government of Indonesia implemented a tight industrial policy package in attempt to re-establish the manufacturing industry as the main driver of economic development. Accordingly, the decomposition of TFP growth will help to provide an understanding of whether gains in the levels of industry productivity are achieved through the efficient use of inputs or through technological progress. From this perspective, the decomposition of TFP growth is expected to elicit a proper analysis of Indonesia's manufacturing productivity, which will aid in the development of effective policies in this area.

The decomposition of productivity change in this study is performed using Färe-Primont productivity index developed by O'Donnell (2010, 2012). This is a relatively new index-based method for measuring and decomposing productivity change. It expands the decomposition of TFP change into broader components that had been previously employed, such as Malmquist productivity index. O'Donnell (2012) proposes a measurement approach which meets all the required axioms of productivity index measurement, so that the Färe-Primont productivity index of O'Donnell (2012) is categorized as a "multiplicatively-complete" productivity index.

This chapter consists of seven sections. Section 6.2 briefly discusses the measurement of TFP growth and its decomposition. Section 6.3 analyses the measures of productivity and efficiency, and this analysis is followed by the decomposition of productivity in Section 6.4. Section 6.5 discusses the data used for estimation. Section 6.6 provides the results and an analysis of TFP change and its decompositions and, finally, a conclusion is presented in Section 6.7.

6.2. The Measurement of TFP and its Decomposition

As discussed in Chapter 4, various methods of measuring TFP growth and its decomposition have been used in numerous studies. In general, the measurement of TFP growth can be classified into two main methods: the frontier approach and non-frontier approach. Technically, these methods can be performed using parametric estimation and non-parametric estimation, in both of which, the estimation procedure is normally conducted within the framework of the production function.

In this regard, O'Donnell (2011a) explains that Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are the two main techniques available for estimating the production frontier. The advantage of using DEA is that it does not require any explicit assumptions regarding the functional form of the unknown production frontier. O'Donnell (2012) mentions that DEA implicitly assumes the production frontier is locally linear. DEA also does not require specific assumptions concerning error terms, there are no statistical issues such as endogeneity, and fast computer packages are available for computing different measures of efficiency. The main drawback of DEA is that it does not allow for statistical noise, so that it cannot distinguish inefficiency from noise. Further, using DEA, it is difficult to compute elasticities of output response and associated economic quantities that involve partial derivatives such as shadow prices. In DEA, the measures of reliability for efficiency scores are difficult to obtain, results may be sensitive to outliers, and technical efficiency estimates are upwardly biased in small samples (O'Donnell 2011a).

In contrast, Stochastic Frontier Analysis (SFA) is an econometric methodology that involves the use of an arbitrary function to approximate the unknown production frontier. The main advantages of SFA are those things not covered by DEA, namely

SFA accommodates errors of approximation and other sources of statistical noise, such as measurement errors and omitted exogenous variables, and making statistical inference is relatively straightforward. The main drawbacks of SFA are that findings may be sensitive to the choice of the functional form used in estimation and the associated assumptions concerning error distributions, and the results may be unreliable if sample sizes are small. SFA may also face the problem of endogeneity (O'Donnell 2011a).

As has been widely acknowledged by scholars, the measurement of productivity using the index approach was initiated by Fisher (1922), Tornqvist (1936) and Malmquist (1953), while Solow (1957) proposed an alternative method using the neoclassical growth model. The frontier approach to TFP growth measurement is an alternative method first introduced by Farell (1957), then formalized in two seminal works by Meeusen and van den Broeck (1977) and Aigner et al. (1977). More recently, the method for measuring TFP growth and its sources have been significantly developed by scholars, as exemplified in the recent index measurement of productivity change proposed by O'Donnell (2012).

In this study, the decomposition of productivity change is performed using the Färe and Primont productivity index proposed by O'Donnell (2012). There are several reasons for using this method. First, O'Donnell's (2012) decomposition method does not require strong assumptions concerning the production technology or the nature of technical change. Second, it also does not require any assumptions about the optimizing behaviour of firms or the degree of competition in products markets. Third, this method decomposes the productivity change into broader sources than previous methods do. Fourth, in Indonesian case studies, no previous studies have applied this method, so employing it will enrich previous findings. Finally, the O'Donnell's (2012) decomposition method can be performed easily using a computer software package namely DPIN 3.0, which was developed by O'Donnell (2011).

6.3. Measures of Productivity and Efficiency

This chapter analyses the decomposition of productivity change within the aggregate quantity framework of O'Donnell (2010, 2012). The following section briefly explains this framework. Let $x_{it}=(x_{1it},\dots,x_{Kit})'$ and $q_{it}=\left(q_{1it},\dots,q_{Jit}\right)'$ denotes the vectors of input and output quantities for firm *i* and period *t*. The TFP of a firm in the aggregate quantity framework of O'Donnell (2011b, 2012) is defined as:

$$TFP_{it} = \frac{Q_{it}}{X_{it}} \quad (6.1)$$

where $Q_{it} \equiv Q(q_{it})$ represents the aggregate output, and $X_{it} \equiv X(x_{it})$ is an aggregate input, and Q(.) and X(.) are non-negative, non-decreasing and linearly-homogenous aggregator functions.

Based on Equation 6.1, the definition means that measures of efficiency and productivity can be defined as ratios of measures of TFP. If the maximum TFP that can be achieved using the technology available in period t is defined as TFP_t^*, then the measure of productive efficiency is the ratio of observed TFP to the maximum TFP that is possible (O'Donnell 2011b, 2012):

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{Q_{it}/X_{it}}{Q_t^*/X_t^*} \leq 1 \qquad \text{(TFP efficiency)} \quad (6.2)$$

where Q_t^* and X_t^* are aggregates of the output and input vectors that maximise TFP. Other measures of efficiency that feature in an input-oriented decomposition of productivity change include (O'Donnell 2011b, 2012):

$$ITE_{it} = \frac{Q_{it}/X_{it}}{Q_{it}/\bar{X}_{it}} = \frac{\bar{X}_{it}}{X_{it}} \leq 1 \qquad \text{(technical efficiency)} \quad (6.3)$$

$$ISE_{it} = \frac{Q_{it}/\bar{X}_{it}}{\tilde{Q}_{it}/\tilde{X}_{it}} \leq 1 \qquad \text{(pure scale efficiency)} \quad (6.4)$$

$$IME_{it} = \frac{Q_{it}/\bar{X}_{it}}{Q_{it}/\hat{X}_{it}} = \frac{\hat{X}_{it}}{\bar{X}_{it}} \leq 1 \qquad \text{(pure mix efficiency)} \quad (6.5)$$

$$ISME_{it} = \frac{Q_{it}/\bar{X}_{it}}{TFP_t^*} \leq 1 \qquad \text{(scale-mix efficiency)} \quad (6.6)$$

where $\bar{X}_{it}$ is the minimum aggregate input of production when using a scalar multiple of x_{it} to produce a scalar output of q_{it}; $\hat{X}_{it}$ is the minimum aggregate input possible using any input vector to produce q_{it}; and $\tilde{Q}_{it}$ and $\tilde{X}_{it}$ are the aggregate output and input obtained when TFP is maximised, subject to the constraint that the output and input vectors are scalar multiples of q_{it} and x_{it} respectively.

O'Donnell (2011b, 2012) mentions that the measures of input-oriented technical and scale efficiency in Equation (6.3) and (6.4) are the standard measures described by Coelli et al. (2005) and Balk (1998). Accordingly, the measures of input-oriented mix and scale-mix efficiency defined by Equation (6.5) and Equation (6.6) are newer measures defined by O'Donnell (2012). The measures of efficiency in Equations (6.3) to (6.6) can also be performed by an output-oriented approach as described in O'Donnell (2011b, 2012).

6.4. Decomposing Productivity

In the aggregate quantity framework of O'Donnell (2012), the productivity index that compares the TFP of firm *i* in period *t* with the TFP of firm *h* in period *s* is defined as:

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Q_{it}/X_{it}}{Q_{hs}/X_{hs}} = \frac{Q_{hs.it}}{X_{hs,it}} \quad (6.7)$$

where $Q_{hs,it} \equiv Q_{it}/Q_{hs}$ is an output quantity index (a measure of output growth) and $X_{hs,it} \equiv X_{it}/X_{hs}$ is an input quantity index (a measure of input growth). Index numbers that can be written in the form of aggregate quantities as in Equation (6.7) are said to be multiplicatively-complete (O'Donnell 2012). Different multiplicatively-complete indexes are obtained by choosing different functional forms for the aggregator functions Q(.) and X(.).

O'Donnell (2012) shows that any multiplicatively-complete TFP index, as in Equation (6.7), can be decomposed into various measures of technical change and efficiency change. A number of decompositions can be made, but the simplest can be performed by decomposing TFP into technical change and efficiency change. Equation (6.2) can be re-written as: $TFP_{it} = TFP_t^* X\ TFPE_{it}$ for $i=1,...,N$ and $t=1,...,T$. It follows that:

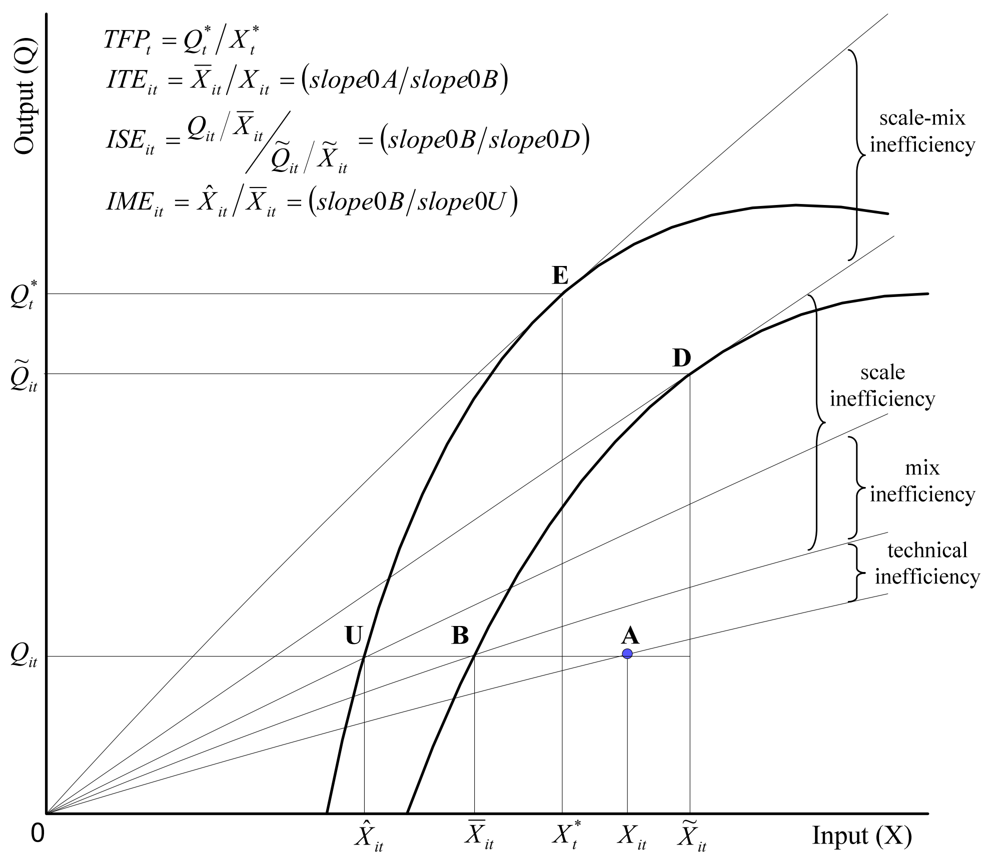
$$TFP_{hs,it} \equiv \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{TFPE_{it}}{TFPE_{hs}}\right) \quad (6.8)$$

The first term in parentheses on the right-hand side of Equation (6.8) compares the maximum TFP possible in period *t* with the maximum TFP possible in period *s*. This term is a measure of technical change or technological progress. The second term from the right-hand side and in parentheses measures the overall efficiency change. The efficiency change component can be further decomposed into various measures of technical, scale and mix efficiency change. For example, overall efficiency change can be decomposed into technical efficiency change and scale-mix efficiency change, so that, based on Equations (6.2), (6.3) and (6.6), the TFP change in Equation (6.8) can be written in the form:

$$TFP_{hs,it} \equiv \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{ITE_{it}}{ITE_{hs}}\right)\left(\frac{ISME_{it}}{ISME_{hs}}\right) \quad (6.9)$$

In Equation (6.9), TFP change can be decomposed into three intrinsically different components: a technical change component that measures movements in the production frontier; a technical efficiency change component that measures movements towards or away from the frontier; and a scale-mix efficiency change component that measures movements around the frontier surface to capture the economies of scale and scope. Several other input- and output-oriented decompositions of TFP change are discussed in O'Donnell (2011b, 2012). This chapter focuses on the decompositions given by Equation (6.8) and Equation (6.9).

Figure 6.1: Input-oriented of the Components of TFP Change



Source: O'Donnell (2012)

To illustrate the decompositions of TFP change diagrammatically, Figure 6.1 shows the input-oriented decompositions of TFP change for several components. In twodimensional perspectives, Figure 6.1 also presents the conventional measures of TFP change that can be calculated from the related slopes of rays through the origin as aggregate quantity space. This figure is important to analyse the movement of firm in maximizing its TFP. For example, if a firm operates its production at point A, input-oriented technical inefficiency is measured as horizontal distance from point A to B. Input-oriented technical efficiency (ITE) is represented as ratio between slope 0A/slope 0B, which also equal to the ratio of TFP at point A to TFP at point B, or ratio of observed TFP to maximum TFP possible with keeping the output vector and input mix fixed (O'Donnell 2012).

In addition, following O'Donnell (2011b, 2012), to solve the productivity index in Equation (6.7), this study uses the Färe-Primont aggregator function, which is non-negative, non-decreasing and linearly homogenous as follows:

$$Q(q)=D_0(x_0,q,t_0) \qquad (6.10)$$

$$X(x)=D_I(x,q_0,t_0) \qquad (6.11)$$

where q and x are vectors of input and output quantities and $D_0(.)$ and $D_I(.)$ are the output and input distance functions. The Färe-Primont productivity index is given (O'Donnell 2012) as:

$$TFP_{hs,it}=\frac{D_O(x_0,q_{it},t_0)}{D_O(x_0,q_{hs},t_0)}\frac{D_I(x_{hs},q_0,t_0)}{D_I(x_{it},q_0,t_0)} \qquad (6.12)$$

6.5. Data

This study computes and decomposes Färe-Primont TFP indexes for 59 industrial sectors at the 3-digit ISIC level over the period 2000–2009. The output variable is output of industry (Y) and input variables are capital (K), labour (L), raw materials (M) and energy (E). The definitions and measurements of these variables are as explained in the Chapter 5. The decomposition of productivity change is performed at the 3-digit ISIC level because it is expected to provide deeper and broader analysis. Previous studies on the decomposition of productivity growth in Indonesian perspective have mostly focused on 2-digit ISIC level, which covers only 23 sub-sector industries. All the data used in this analysis are obtained from Statistics Indonesia *(Badan Pusat Statistik – BPS)*.

6.6. Results and Analysis

The decomposition method as described in Sections 6.4 and 6.5 is performed using DPIN 3.0 program developed by O'Donnell (2011). DPIN uses the DEA program of O'Donnell (2011) to estimate the Färe-Primont TFP index given by Equation (6.7) and the components of TFP change in Equation (6.8) and Equation (6.9). The estimation includes the technical, scale and mix efficiency scores as presented in Equations (6.3) to (6.6).

The DEA linear program (LP) is non-parametric, as it does not involve any error terms, meaning that it does not involve assumptions about the distribution of parameters, such as the means and variances of the distribution of these error terms. The term non-parametric should not be interpreted as indicating that DEA is free of any assumptions regarding the functional form of the production frontier. Rather, in this approach, DEA is underpinned by the assumption that the frontier is locally linear (O'Donnell 2011). In this analysis, DPIN is set to allow for technical progress in some years and technical regress in others, as well as variable returns to scale.

6.6.1. TFP Change and Efficiency Change 2000–2009

Färe-Primont estimates the technical change and efficiency change components of the TFP change over the period 2000 to 2009 are presented in Table 6.1. The estimated technical change component of the TFP index depends on the assumptions about production technology that are chosen (O'Donnell 2011b). The Färe-Primont estimates in Table 6.1 are results under the assumption that production technology exhibit variable returns to scale (VRS) and that in any given period, all sectors experience the same rate of technical change.

In Table 6.1, for period 2000–2009, $\Delta TFP^{*} = 1.0358$, which equates to an average rate of technical progress of $\Delta lnTFP^{*} = \frac{ln(1.0358)}{(2009\text{-}2000)} = 0.003908$ or 0.3908% per annum.

The production possibility set is also allows both expansion and contraction. This means that technological progress can take place in some periods and technical regress can take place in others (O'Donnell 2011b).

Table 6.1 shows the estimates of the average technical change and the average efficiency change components of the TFP for all industries. This table indicates that during the period 2000 to 2009 the TFP in the manufacturing industry increased by 2.132% due to the combined effects of technical progress of 3.58% and a fall overall in efficiency of 1.3998% (i.e., dTFP = dTFP* x dTFPE = 1.0358 x 0.9860 = 1.0213). The table also reveals that the fall in overall efficiency is due to the decreases of scale-mix efficiency of 1.142% and a fall in technical efficiency of 0.261% (i.e., dTFPE = dITE x dISME = 0.9974 x 0.9886 = 0.9860). Thus, the improvement of TFP during 2000 to 2009 is mostly driven by improvements of technical change. Meanwhile, scale-mix efficiency and technical efficiency decreased.

Table 6.1: Annual TFP Change, Technical Change and Efficiency Change 2001–2009[12]

Year	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)
	(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)
2001	0.9972	0.9973	0.9999	0.9903	1.0097
2002	1.0012	0.9947	1.0065	1.0126	0.9940
2003	0.9998	0.9875	1.0125	0.9998	1.0127
2004	1.0075	0.9831	1.0249	1.0153	1.0095
2005	0.9987	1.0289	0.9706	0.9944	0.9761
2006	0.9997	0.9992	1.0006	0.9845	1.0163
2007	0.9997	0.9852	1.0148	0.9995	1.0152
2008	0.9968	1.0004	0.9964	1.0077	0.9888
2009	1.0207	1.0616	0.9615	0.9937	0.9675
2000-2004	1.0057	0.9630	1.0444	1.0179	1.0260
2005-2009	1.0169	1.0454	0.9727	0.9854	0.9871
2000-2009	1.0213	1.0358	0.9860	0.9974	0.9886

Source: Author's calculation using DPIN 3.0.

In general, from 2000 to 2009 TFP change in the manufacturing industry tended to fluctuate. The highest improvement in TFP took place in 2009, i.e. by 2.072%. This is mainly due to the combined effects of an improvement in technical of 6.159% and the fall in overall efficiency of 3.855%. The lowest level of the TFP improvement is in 2008, when the TFP decreased by 0.315% due mostly to the fall in overall

[12] A more comprehensive decomposition of TFP change is presented in Appendix 6.1 and 6.2. Year 2001 means the change of TFP index of 2001 relative to 2000 and so on. For example, in year 2002 TFP change is 1.0012, meaning that TFP increased by 0.12% in 2002, which is calculated from (1.0012-1)*100. Meanwhile, technical change is 0.9947, meaning that technical decreased by 0.53% in 2002, which is calculated from (0.9947-1)*100.

efficiency of 0.358%. In accordance to Table 6.1, Figure 6.2 presents the pattern of TFP change and its components for the period 2000 to 2009.

Another important feature from Table 6.1 is that during the period 2000 to 2004 TFP increased by 0.570%, driven by the improvement of overall efficiency 4.437%. This improvement was due to the combined effect of an improvement in scale-mix efficiency of 2.603% and the increase in technical efficiency of 1.787%. However, the technical change index in the period from 2000 to 2004 decreased by 3.700%. In addition, in the period 2005 to 2009, the TFP increased by 1.69%, due to the technical progress by 4.54% and the decrease in the overall efficiency by 2.731%.

These two abovementioned periods are important because in that period the government released different industrial policies. As mentioned in Chapter 2, in 2000 the government announced a "quick response" industrial policy, which aimed to strengthen the manufacturing industry after the severe from economic crisis in 1998. It was followed by a more comprehensive industrial policy package, namely the "Medium and Long Term National Industrial Development Policy", in 2005. In brief, these policies seem to have had a positive influence on industrial development and performance, as there was an improvement in TFP during 2000 to 2009. However, the increase in TFP in 2005–2009 was larger than in the period 2000–2004. The reason is that technical change significantly improved in the latter period, which indicates that the level of technology employed in manufacturing industry improved. This situation is in line with the government's long-term design for industrial development, which seeks to make the manufacturing industry increasingly technology-based. By 2025, it is planned that manufacturing industries will be primarily "high-tech" industries.

Figure 6.2: TFP Growth and its Components 2001 to 2009 (%)

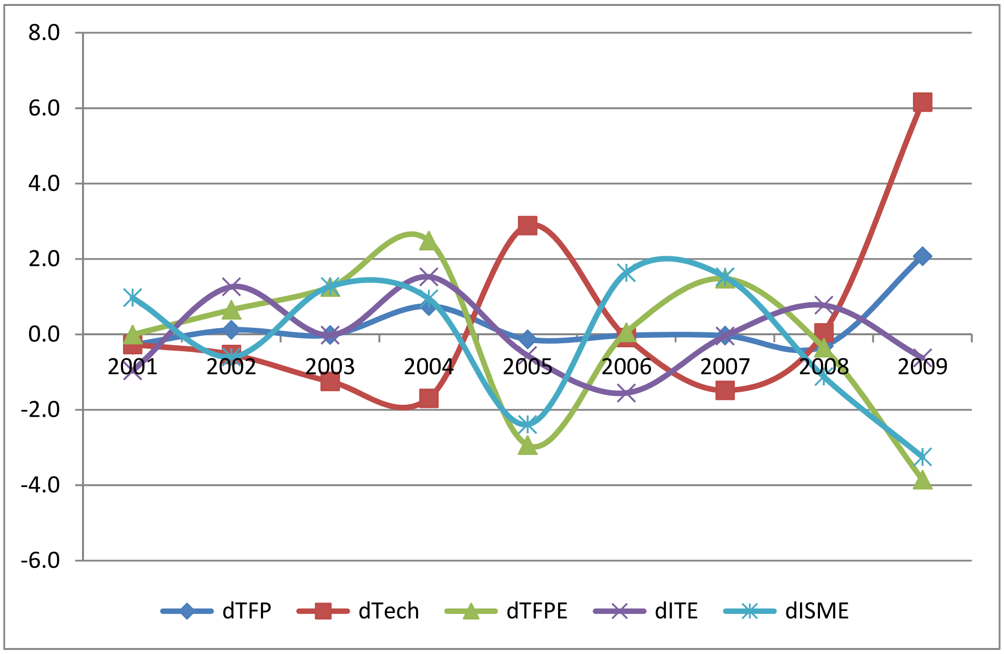


Figure 6.2 shows the movement of TFP change and its components from 2001 to 2009. Technical change (dTECH) fluctuates, but improves substantially in 2005 and 2009. Technical change contributed the most to TFP growth in these periods. Moreover, the movement of technical (dTECH) appears to have been in opposite direction to the movement of scale-mix efficiency (dISME). This indicates that firms have not been able to synergize these two components to support productivity growth. When the level of technology is stable (without improvement), firms are able to exploit their economies of scale to drive productivity. However, when there is an improvement in the use of technology, this is not followed by improvements in economies of scale. The possible reason for this is that the movement of the production frontier due to the technological upgrading creates a gap between best-practice technology and the technology actually in use.

In addition, Table 6.2 presents a summary of the estimates of TFP change and their components from 2000 to 2009. There, the TFP change and their components follow no specific path. Technical progress was largely occurred in 2008 and 2009. It contributes substantially to average overall TFP change, enabling this to be positive. The results indicate that the technical progress after the economic crisis 1998 was gradual. In 2005, it increased but then declined before increasing again in 2008 and 2009. The fluctuating TFP change and their components during this period may also have been influenced by national and global economic trends, such as the increasing oil price and the global financial crisis in 2008. Although Indonesia's economy was among the more stable, it cannot be denied that the macroeconomic shock affected the performance of the manufacturing industry.

Table 6.2: The Summary of TFP Change and Efficiency Change 2000–2009

Year	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)
	(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)
2001/2000	-	-	-	-	+
2002	+	-	+	+	-
2003	-	-	+	-	+
2004	+	-	+	+	+
2005	-	+	-	-	-
2006	-	-	+	-	+
2007	-	-	+	-	+
2008	-	+	-	+	-
2009	+	+	-	-	-
2000-2004	+	-	+	+	+
2005-2009	+	+	-	-	-
2000-2009	+	+	-	-	-

Note: (+) sign if TFP/Efficiency change ≥ 1 (increase); (-) sign if TFP/Efficiency change < 1 (decrease).

In general, the results of the decomposition of TFP growth in Table 6.1 are in line with the previous studies, such as those of Margono and Sharma (2006) and Ikhsan (2007), who used the traditional divisia-index and the stochastic frontier analysis (SFA) as proposed by Khumbakar and Lovell (2000). They are also consistent with the results of Suyanto et al. (2009), who used Malmquist productivity index. Any differences are in the scores only. For example, Ikhsan (2007) found aggregate TFP growth in the manufacturing industry of 1.55 percent for the period 1988 to 2000. The major contributor was the technological progress (dTECH). Similarly, Suyanto et al. (2009) found a positive TFP growth of 2.33 percent for the period 1988 to 2000 and 1.55 percent for the period 1997 to 2000. However, the results in this study differ to those of Aswicahyono and Hill (2002). Using the growth accounting method, they found TFP growth of -4.9 percent for 28 industrial sectors over the period 1981 to 1993.

The results of the decomposition of TFP growth in Table 6.1 can be further explained as follows. Various factors possibly affected the behaviour of TFP growth during the period 2005 to 2009. One of them, perhaps, is the influence of the government's industrial policies that began after the economic crisis in 1998. After the crisis, the government released a series of industrial policies that sought to accelerate the process of industrial recovery and to stimulate high growth in the manufacturing industry. In the proposed timeframes associated with these policies, the period 2004 to 2009 was anticipated as being period when rapid growth would be achieved, largely driven by increased use of technology.

The series of government industrial policies commenced in 2001, and other policies were introduced in 2004 and 2008. One important thing, these policies sought to do was provide adequate industrial facilities and numerous opportunities for firms to improve and increase their use of technology. Financial support was provided to firms for adopting new machinery, particularly in prominent industries such as food, textiles and other related industries.[13] However, these technologies may not yet have been applied at the optimal levels of scale, so they have contributed negatively to firm-level technical efficiency. In such conditions, the production function may have moved upwards, but at the same time a larger gap from the frontier may have been generated.

6.6.2 Highest-TFP by Industry 2000–2009

Before discussing the TFP change and their components in sub-sectors industry, the findings in terms of levels will first be discussed. Table 6.3 shows the highest TFP industry for each year from 2000 to 2009. The analysis of this table follows the approach of Laurenceson and O'Donnell (2011). In general, the results are intuitively reasonable with respect to the development of manufacturing industry from 2000 to 2009. Four industries in Table 6.3 can be classified as the heavy engineering or technological industries, i.e. electrical accumulator and battery (ISIC 314), motor vehicles with four wheels or more (ISIC 341), communications equipment (ISIC 322), and office accounting, data processing machineries and equipment (ISIC 300).

[13] For example, according to a survey conducted by the Ministry of Industry, around 70 percent of the machinery in the textiles and textile-products industry was more than twenty years old in 2007, and needed to be replaced by new machines (Ministry of Industry Republic of Indonesia 2007).

Table 6.3: Highest-TFP by Industry 2000–2009

Year	ISIC	Industry
2000	314	Electrical accumulator and battery
2001	341	Motor vehicles
2002	341	Motor vehicles
2003	341	Motor vehicles
2004	341	Motor vehicles
2005	341	Motor vehicles
2006	341	Motor vehicles
2007	322	Communication equipment
2008	300	Office accounting and data processing machinery and equipment
2009	300	Office accounting and data processing machinery and equipment

Source: Author's calculation using DPIN 3.0.

These industries have been recognized as the emerging sectors in Indonesia, especially after economic crisis in 1998. They grow as the prominent sectors whose importance at the national level will be similar to the current prominence of the food and beverages, textiles and tobacco industries. Therefore, these industries are expected to be the main driver of economic growth in the future. As mentioned in the long-term industrial policy, three groups of industries have been identified by the government as the future leading sectors; these are agro-industry, transportation and the electronics industry.

There are several plausible explanations as to why these industries listed in Table 6.3 reach highest TFP. The motor vehicles industry (ISIC 341) and its markets, for example, grew significantly after the 1998 economic crisis. According to the industrial report published by the Ministry of Industry Republic of Indonesia[14], the transportation and machinery industry was the sector that experienced the highest growth from 2004 to 2009 compared to other industries. In 2009 its growth was 8.75%, while the overall manufacturing growth reached only 3.97%. Manufacturing growth has to large degree been driven by the transportation and machinery industries. This sector was markedly different to the textiles industry, which declined by 5.15% in 2009. Moreover, in 2009, the contribution of motor vehicles industry

[14] Industrial Development Report 2004–2009 *(Laporan Pengembangan Sektor Industri Tahun 2004–2009)*, Ministry Industry Republic of Indonesia (http://www.kemenperin.go.id/kinerja-industri)

(ISIC 341) to the total manufacturing industry was 28.95%, the second highest contribution after the food, beverages and tobacco industry (30.91%).

The growing automotive market in Indonesia in the last ten years offered numerous opportunities. It led to accelerated production, not only to cover domestic demand but also to supply the export market. The growing demand has been stimulated by increased middle-class income and the marketing strategies of car producers, in which they have been producing reasonably-priced vehicles for consumers. Data from *Gaikindo* (The Association of Indonesian Automotive Industries)[15] shows that overall automotive production for all types of cars increased consistently from 2000 to 2009. For the domestic market, automotive production increases from 300,965 units in 2000 to 603,774 units in 2008, but slightly decreased to 483.548 units in 2009, due to the impact of the global financial crisis in 2008 and the spike in the oil price in the international market. However, the market rebounded in 2010, with production reaching 764,710 units. For the export market, total production increased from 121,175 units in 2005 to 204,692 units in 2009. The growth in production could be seen as supporting the introduction of new technology through equipment investment that contributed to the industry achieving the highest TFP growth of an industry for several years.

Likewise, the industry of communication equipment (ISIC 322), which is included in the telecommunications sector, grew remarkably during 2000 to 2009. The industrial report provided by the Ministry of Industry Republic of Indonesia[16], notes that the Indonesian telecommunications industry is among the fastest growing in the world. In 2008, for example, Indonesia became the third largest telecommunications market in Asia, having 140.2 million mobile telephone subscribers. It is behind only China with 615.7 million subscribers and India with 346.8 million subscribers. According to research conducted by Mobil World Database, Indonesia is in sixth place in its top 20 mobile market rankings in the world, above several developed countries, such as Germany, Japan and Italy. Such market conditions are conducive to the industry of communications equipment (ISIC 322) achieving high TFP. Figure 6.3 shows the comparison of TFP levels for those industries that achieved the highest TFP from 2000 to 2009.

[15] http://gaikindo.or.id/
[16] Industry: Facts and Figures 2011, Ministry of Industry Republic of Indonesia (http://www.kemenperin.go.id/majalah/11/facts-and-figures-industri-indonesia)

Figure 6.3: Levels of Productivity by Industry 2000–2009

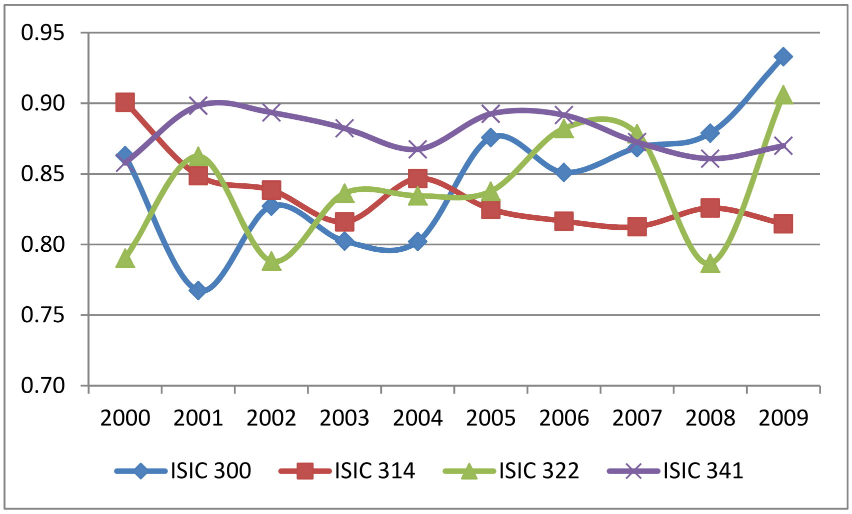


Figure 6.3 shows that the productivity levels of the industry of office accounting, data processing machinery and equipment (ISIC 300) tended to consistently increase after declining in 2001, and achieved its maximum levels in 2008 and 2009. Conversely, the productivity levels of the electrical accumulator and battery industry (ISIC 314) consistently declined after having the highest levels in 2000. The motor vehicles industry (ISIC 341) was the sector which most often attained the highest productivity levels.

6.6.3. TFP Change, Technical Change and Efficiency Change by Industry

This section discusses the TFP change and efficiency change by industry. The discussion focuses only on the industries that display relevant characteristics to the progress of industrial development during 2000 to 2009. Table 6.4 shows the ten selected industries that experienced relatively high change in TFP[17]. Some important features of Table 6.4 are discussed in the following sub-section.

The industries that experienced relatively high TFP changes in 2000 to 2009 were predominantly heavy engineering and technology intensive industries. These industries have been earmarked by the government to be main pillars of future industry in Indonesia. The government has comprehensively supported these industries through particular industrial policies. As mentioned in Presidential Decree No 28/2008 on the National Industrial Policy, industries such as agro-based industry, transportation, information technology and the telecommunications equipment

[17] TFP change and efficiency change for all industries in 3-digit ISIC are presented in Appendix 6.2.

industry are given first priority. This industrial group is considered more sustainable because it relies on knowledge and skilled-labour, renewable natural resources and technological mastery (Ministry of Industry Republic of Indonesia 2011).

To realize its industrial development program, the government has initiated policies such as: developing a comfortable and conducive business environment and the development of innovation capabilities; strengthening the linkage between all levels of value of related industry clusters; increasing resources' capabilities used in an industry to develop its main competence; determining the industry distribution priority; and developing small and medium-sized industries (SMEs). To compete successfully in international market, the long-term industrial development focuses on increasing research capability and development, and increasing the skills and expertise of human resources for innovation in processes and products (Ministry of Industry Republic of Indonesia 2011).

Table 6.4: The Improvement of TFP in Selected Manufacturing Industries 2000–2009

No	KLUI (ISIC)	Industry	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)
			(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)
1	322	Communications equipment	1.1463	1.0358	1.1067	1.0581	1.0460
2	300	Office accounting and data processing machinery and equipment	1.0813	1.0358	1.0439	1.0000	1.0439
3	342	Motor vehicles' bodies	1.0688	1.0358	1.0318	0.9875	1.0448
4	222	Printing and activities related to printing	1.0595	1.0358	1.0228	1.0301	0.9928
5	323	Radio, television, sound and picture recordings and other similar activities	1.0495	1.0358	1.0131	1.0260	0.9875
6	292	Special purpose machinery	1.0462	1.0358	1.0101	1.0378	0.9733
7	273	Metal smelting	1.0429	1.0358	1.0068	1.0456	0.9629
8	264	Cement, lime plaster and gypsum	1.0423	1.0358	1.0063	0.9841	1.0225
9	241	Industrial chemicals	1.0379	1.0358	1.0020	0.9874	1.0149
10	151	Processing and preserving of meat, fish, fruits, vegetables, cooking oil and fat	1.0371	1.0358	1.0012	1.0000	1.0012

Source: Author's calculation using DPIN 3.0.

In accordance with the preceding discussion, the trend of industrial growth in Table 6.5 below may help to explain why the heavy engineering and technology intensive industries experienced high positive TFP change from 2000 to 2009.

Table 6.5: Percentage Growth of Manufacturing Industry (excluding oil and gas) 2004-2009

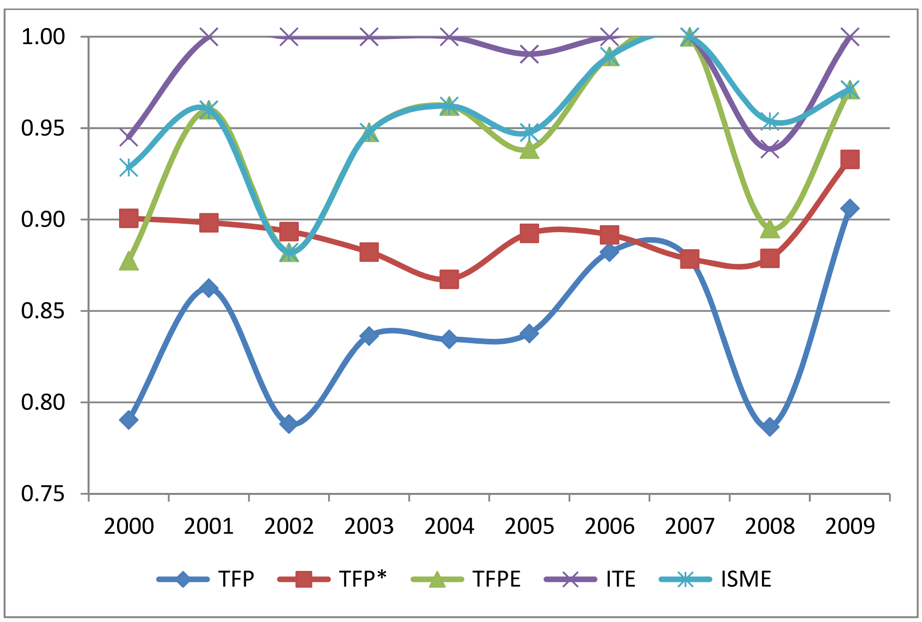
Industry	2004	2005	2006	2007	2008	2009
Food, beverages and tobacco	1.39	2.75	7.22	5.05	2.34	3.66
Textiles, leather products and foot wear	4.06	1.31	1.23	-3.68	-3.64	-5.15
Wood products	-2.07	-0.92	-0.66	-1.74	3.45	2.44
Paper and printing products	7.61	2.39	2.09	5.79	-1.48	0.61
Fertilizer, chemicals and rubber products	9.01	8.77	4.48	5.69	4.46	3.5
Cement and non-metal mineral products	9.53	3.81	0.53	3.4	-1.49	-1.5
Basic metals, iron and steel	-2.61	-3.7	4.73	1.69	-2.05	0.55
Transportation, machinery and equipment	17.67	12.38	7.55	9.73	9.79	8.75
Others	12.77	2.61	3.62	-2.82	-0.96	-2.82
Total Industry	7.51	5.86	5.27	5.15	4.05	3.97

Source: Industrial Development Report 2004–2009, the Ministry of Industry Republic of Indonesia.

Table 6.5 shows the percentage growth rate of various manufacturing industries from 2004 to 2009, excluding oil and gas. It indicates that the industry of transportation, machinery and equipment had the highest level of growth. Even though its growth levels declined due to the impacts of macroeconomic and global shocks at the end of this period, the sector was able to sustain its growth. A similar trend can be seen in the fertilizer, chemicals and rubber products industry, but with lower growth rates. In light of the above performance, it is not surprising that these industries enjoyed positive TFP change for the period 2000 to 2009.

Moving to a deeper analysis of TFP change at the 3-digit industry level, two industries which recorded the highest TFP growth for particular years (see Table 6.3), i.e. communications equipment (ISIC 322) and office accounting and data processing machinery and equipment (ISIC 300) are also in the group of industries that experienced high TFP change. From Table 6.4, it can be seen that ISIC 322 was the industry that had the greatest TFP change from 2000 to 2009, with 14.63%. The change was driven positive technical change (dTECH) of 3.58% and the overall efficiency change (dTFPE) of 10.67% (i.e. dTFP = dTECH x dTFPE = 1.0358 x 1.1067 = 1.1463). The improvement of overall efficiency change was due to the increase in technical efficiency (dITE) and scale-mix efficiency (dISME), these being 5.81% and 4.60% respectively (i.e. dTFPE = dITE x dISME = 1.0581 x 1.0460 = 1.1067). Thus, all the components of TFP change in this sector improved. By comparison, ISIC 300 experienced TFP change of 8.13%, which was due to a combination of technical change and efficiency change of 3.58% and 4.39% respectively (i.e. dTFP = dTECH x dTFPE = 1.0358 x 1.0439 = 1.0813). To illustrate, Figure 6.4 presents the Färe-Primont estimates of levels of TFP for the communication equipment industry (ISIC 322). The figure shows the movement of TFP, declining twice in 2002 and 2008 before achieving substantial improvement in 2009.

Figure 6.4: Levels of Productivity and Efficiency in Communications Equipment Industry (ISIC 322) 2000–2009



Further results show that of all chemical industries, the industrial chemicals industry (ISIC 241) recorded the highest TFP change in this period. It increased by 3.79% due to the technical change of 3.58% and of efficiency change of 0.20%. In this case, efficiency change was completely driven by the scale-mix efficiency change of 1.49%. This was the case because, technical efficiency decreased by 1.26% (i.e. dTFPE = dITE x dISME = 0.9874 x 1.0149 = 1.0020). As presented in Table 6.5, the chemical industry is one of the industries that achieved a relatively high TFP change.

This sector also makes an important contribution to the output of the entire manufacturing industry. In 2009, for example, the contribution of the chemical and fertilizer industry was 13.52%, the third largest contribution after food, beverages and tobacco (30.91%) and transportation, machinery and equipment (28.95%) (Ministry of Industry 2011).

Another interesting feature is the pattern of TFP change seen in light industry for the period 2000–2009. Unlike heavy engineering and technological industries or highly capital intensive industries, light industry is predominantly labour-intensive. In Table 6.4, the industry of processing and preserving of meat, fish, fruits, vegetables, cooking oil and fat (ISIC151) has one of the higher levels of TFP change among light industries. TFP change in this industry was by 3.71% due to technical change (dTECH) of 3.58% and efficiency change (dTFPE) of 0.12%. The improvement in efficiency was driven by the increase in scale-mix efficiency (dISME) of 0.12%, since there was no movement in the technical efficiency (dITE) (i.e. dTFPE = dITE x dISME = 1.000 x 1.0012 = 1.0012).

Continuing the discussion of TFP change and its components, Table 6.6 below presents the TFP change and efficiency change for selected manufacturing industries at the 3-digit ISIC level that experienced low or decreased TFP change during 2000 to 2009. The following discussion analyses some important aspects of these results. One of the surprising results is that the electrical accumulator and battery industry (ISIC 314) was the sector which experienced the greatest reduction in TFP change, even though this sector achieved highest TFP index in 2000 (see Table 6.3). The TFP (dTFP) decreased by 9.54% due to a significant decline in overall efficiency (dTFPE) of 12.68%. This was despite the fact that the technical change index (dTECH) increased by 3.58% (i.e. dTFP = dTECH x dTFPE = 1.0358 x 0.8732 = 0.9046). In detail, the decline in overall efficiency was due to reduced technical efficiency (dITE) and scale-mix efficiency (dISME) by 7.640% and 5.451% respectively (i.e. dTFPE = dITE x dISME = 0.9236 x 0.9455 = 0.8732).

Table 6.6 also shows that among the industries that experienced a decline in TFP are industries which have relatively stagnant market conditions, such as goods made from asbestos (ISIC 266), non-classified household tools (ISIC 293), glass and goods made from glass (ISIC 261), goods made from stone (ISIC 265), the other processing' industry (ISIC 369) and publishing (ISIC 221). These industries are important in terms of their absorption of labour, but they have only a small output share of all manufacturing industries. Given this, it is no surprise that they recorded a decline in TFP. However, when explored more deeply, it can be seen that not all the components of TFP in these industries declined. Table 6.6 columns (4) and (5) show how the interaction between technical efficiency change (dITE) and scale-mix efficiency change (dISME) influenced the overall efficiency change (dTFPE).

Perhaps a more interesting feature of Table 6.6 is the declining TFP for the industry of milk and food made from milk (ISIC 152). This industry has a very large market. With the Indonesian population number reaching around 237 million in 2010 (Statistics Indonesia 2010)[18], the country has become a potentially huge market for milk products. However, this industry relies heavily on the imported raw materials, which account for approximately 70 to 75% of total materials used in production. The result is that this sector depends highly on the fluctuations of the exchange rate. Further, milk and milk products also rely on the high levels of technology, which is very expensive for businesses to invest in. At the level of small-scale size of production, this industry is very sensitive to changes in production cost, which affect the rates of profit. Consequently, the current market for dairy products cannot be fully filled by domestic products, but still depends on imported products. These market conditions may have contributed to the industry of milk and food made from milk (ISIC 152) experiencing a downturn in TFP throughout 2000 to 2009.

[18] http://www.bps.go.id/menutab.php?tabel=1&kat=1&id_subyek=12

Table 6.6: Negative TFP Change in Selected Manufacturing Industries 2000–2009

No	KLUI (ISIC)	Industry	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)
			(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)
1	314	Electrical accumulator and battery	0.9046	1.0358	0.8732	0.9236	0.9455
2	266	Goods made from asbestos	0.9268	1.0358	0.8947	0.8920	1.0030
3	293	Non-classified household tools	0.9529	1.0358	0.9200	0.9984	0.9213
4	321	Electronic tubes and valves and other electronic components	0.9750	1.0358	0.9413	0.9753	0.9652
5	152	Milk and food made from milk	0.9838	1.0358	0.9497	1.0011	0.9487
6	261	Glass and goods made from glass	0.9838	1.0358	0.9498	0.9179	1.0348
7	265	Goods made from stone	0.9861	1.0358	0.9520	0.9323	1.0212
8	369	Other processing	0.9905	1.0358	0.9562	1.0190	0.9382
9	331	Medical, measuring, testing and other equipment except optical equipment	0.9950	1.0358	0.9605	0.9417	1.0199
10	221	Publishing	0.9952	1.0358	0.9608	0.9570	1.0039

Source: Author’s calculation using DPIN 3.0.

In Table 6.6, the negative TFP change of 1.624% for ISIC 152 is associated with a decline in overall efficiency by 5.03% (i.e. dTFPE = dITE x dISME = 1.0011 x 0.9487 = 0.9497). Technical efficiency change (dITE) increases, but the scale-mix efficiency (dISME) declines, indicating that there is a barrier that prevented the scale of production from operating at its optimum level. The downturn of consumer demand is considered to have caused the decline in the scale of production of this industry. It should be noted that, some critical factors affected to the market for milk and dairy products during the period 2000 to 2009; for example, the price hike of the products. As reported by Statistics Indonesia, the price index of this industry has increased by an incredible 85.33% from 2004 to 2008. It is quite likely that this led consumers to reduce their demand for milk and dairy products (Statistics Indonesia 2010).

In general, most manufacturing industries at the 3-digit ISIC level experienced a positive TFP change in the period 2000 to 2009. Of the 59 industrial sectors included in the analysis (see Appendix 6.2), only 12 industries experienced a negative TFP change, suggesting that the industrial policy and development strategy implemented by the government had a positive impact. Since the estimation technique constrains all industries to experience the same technical change (dTECH), the variation in TFP change (dTFP) is determined by the interaction of technical efficiency change (dITE) and scale-mix efficiency change (dISME).

6.7. Conclusion

This chapter discusses the decomposition of TFP change and its components over the period 2000 to 2009 in fifty-nine manufacturing industries at the 3-digit ISIC level. The method used is the Färe-Primont productivity index as proposed by O'Donnell (2010, 2012). The Färe-Primont estimates in this study result from the assumption that production technology exhibits variable returns to scale (VRS) and that in any given period all sectors must experience the same estimated rate of technical change. The average rate of technical change is 0.3908% per annum. The production possibilities set is also permitted to both expand and contract, meaning that technical progress can take place in some periods and technical regress can take place in others (O'Donnell 2012).

The results of estimation show that over the period of 2000 to 2009 TFP in the manufacturing industry increased by 2.132% due to the combined effects of technical progress of 3.58% and negative efficiency improvement of 1.3998%. Further, the results reveal that the decline in overall efficiency was due to decreases in scale-mix efficiency of 1.142% and in technical efficiency of 0.261%. Thus, the improvement of TFP during 2000 to 2009 was driven by the improvement in technical change. From 2000 to 2009 TFP in the manufacturing industry tended to fluctuate. The highest improvement in TFP was 2.072 % in 2009, due to the mixed effects of technical change improvement of 6.159% and decreased overall efficiency of 3.855%. The lowest level of TFP change was in 2008, when it decreased by 0.315%, due largely to the fall of overall efficiency of 0.358%.

Two periods of industrial policies impacted on TFP, each with different consequences. In 2000 to 2004 TFP increased by 0.570%, which was driven by the improvement of overall efficiency by 4.437%. Improved of overall efficiency was due to the combined effect of scale-mix efficiency improvement of 2.603% and the increase of technical efficiency by 1.787%. However, the technical in the period 2000 to 2004 decreased by 3.700%. In addition, in the period 2005 to 2009, the TFP increased by 1.69% due to technical change of 4.54% and overall efficiency improvement by 2.731%.

At the sector level, four industries achieved the highest level of TFP change during 2000 to 2009, were in the heavy engineering and technology industries, such as the motor vehicles (ISIC 341), communication equipment (ISIC 322) and office accounting, data processing machinery and equipment (ISIC 300). The communication equipment industry (ISIC 322) was the industry that recorded the highest of TFP change for the period 2000 to 2009. The increase of 14.63%, was driven by technical change (dTECH) of 3.58% and an overall efficiency change (dTFPE) of 10.67%. The increase in overall efficiency was due to the rise in technical efficiency (dITE) and scale-mix efficiency (dISME) of 5.81% and 4.60% respectively.

Conversely, electrical accumulator and battery industry (ISIC 314) experienced the lowest TFP change, even though this sector achieved the highest TFP change in 2000. The TFP (dTFP) fell by 9.54%, due primarily to a significant decline in overall efficiency (dTFPE) by 12.68%, more than offsetting positive technical change (dTECH) of 3.58%. In further detail, the decline of overall efficiency was due to the downturn in technical efficiency (dITE) and scale-mix efficiency (dISME) by 7.640% and 5.451% respectively.

From an industrial policy perspective, it is important to analyse productivity change and its decomposition in the manufacturing industry, since these changes can be used to identify the nature and the path of productivity change in each industrial sector. Improvements in productivity are a crucial pre-condition for sustainable improvement in standards of living (O'Donnell 2011b), so the precise analysis of productivity growth in the manufacturing industry is needed in order to identify the drivers of the improvement of overall economic productivity in Indonesia. In particular, the movements in productivity from 2000 to 2009 have been seen to be in line with the industrial policies set by the government.

Preliminary evidence for this can be seen in the improvement of the TFP change in the heavy engineering and technology industry from 2000 to 2009 such as communication equipment (ISIC 322), data processing machinery and equipment (ISIC 300), motor vehicles bodies (ISIC 342) and radio, television, sound and picture recording (ISIC 323). However, the TFP change in agro-industries (agro-based manufacturing industries) was slow or stagnant. This indicates that not all industries prioritized by the government experienced the same level of TFP change during 2000 to 2009. The government needs to pay closer attention to these industries, so that agro-based manufacturing industries can also reach their optimum levels of productivity.

In summary, in productivity analysis it is common to estimate reduced-form relationships between TFP indexes and series of variables that are known to influence economic activities (O'Donnell 2011b). In accordance with the main topic of this research, the following chapter will estimate the relationship between TFP growth and variables which are considered to affect this. The analysis will proceeds in the light of agglomeration and spatial economics.

Chapter 7

The Effect of Agglomeration Economies on Productivity Growth

7.1. Introduction

The two previous chapters discuss interrelated topics regarding total factor productivity (TFP). Chapter 5 discusses the effects of agglomeration economies upon firm-level productive efficiency. A one-stage estimation method using a stochastic production frontier (SPF) is employed, following Battesse and Coelli (1995). Chapter 6 discusses the decomposition of total factor productivity growth into various finer efficiency measurements including technical change, scale efficiency change, and technical efficiency change using the Färe-Primont productivity index proposed by O'Donnell (2012).

This chapter continues the two previous chapters' discussion by focusing the analysis on the effect of agglomeration economies upon firm productivity growth. The findings in Chapter 5 confirm that specialization (or the existence of MAR externalities) is more favourable for stimulating firm-level technical efficiency than diversity (or Jacobs' externalities). Since technical efficiency is one of the sources of total factor productivity, it is important to perform further analysis on the relationship between agglomeration economies and total factor productivity (TFP) growth.

Agglomeration economies are generally known as location-specific economies (McCann 2008). Agglomeration is one of the key processes that stimulates productivity in manufacturing activities. The empirical debate among scholars focuses on whether specialization or diversity of economic activities promotes productivity growth. In more specialized regions, knowledge spillovers among firms arise from localization economies, while in more diverse regions, knowledge spill-overs arise from urbanization economies (Martin et al. 2011). Despite the fact that identifying the mechanisms of these relationships is challenging and contentious, empirical findings show that agglomeration economies exert positive effects on firm productivity, as found in the studies of Ciccone and Hall (1996), Henderson (2003), and Mare and Timmins (2007). However, Rosenthal and Strange (2004) emphasize that we do not yet have adequate knowledge about agglomeration economies, sustaining an on-going debate on industrial geographic concentration and the scope of agglomeration economies. To contribute to this debate, this chapter examines the effects of agglomeration economies upon total factor productivity growth using firm-level data from Indonesian manufacturing industries from 2000 to 2009.

The reminder of this chapter is organized in the following order: Section 7.2 briefly discusses the nature of agglomeration economies and productivity growth. Section 7.3 describes the empirical model, followed by a discussion of the estimation method in Section 7.4. Section 7.5 outlines the data sources and measurement of variables, while discussion of the results and empirical analysis are presented in Section 7.6. Finally, Section 7.7 concludes the chapter.

7.2. Agglomeration Economies and Productivity Growth

The question of whether agglomeration economies have positive effects on firm productivity has stimulated on-going discussion among scholars (Moomaw 1981; Ciccone and Hall 1996). In-depth analysis using firm-level data has drawn a good deal of attention from researchers in the wake of Henderson's (2003) seminal work. In general, previous studies on agglomeration economies used aggregate-level data in their analysis, while Henderson (2003) uses firm-level data.

There are several benefits of using firm-level data: First, the theory behind agglomeration economies is micro-economic in nature. It discusses the behaviour of individual economic agents and how the external environment affects them. Second, a firm-level approach provides us with the opportunity to estimate the effects of firms' external local environments on their productivity levels, including a set of firm attributes (Andersoon and Lööf 2011).

Marshall (1920) pioneered to formulation of the benefits that firms derive from being located in close proximity. He argues that external economies are the main source of the advantages enjoyed by firms that are located close together. The emergence of these economies is stimulated by knowledge and information spillovers, labour pooling, and backward and forward linkages among firms.

Ohlin (1933) and Hoover (1937) expand Marshall's idea and propose a broader concept by distinguishing between localization economies and urbanization economies. Urbanization economies refer to external economies in broader urban regions with more diversified economy. On the one hand, localization economies can be viewed as external to the firm but internal to the industry in a specific region.

They are also often associated with specialization phenomena. On the other hand, the nature of urbanization economies is that they are external to the firm, but internal to the whole region, such that they are able to provide benefits to all firms located in the region (Anderson and Lööf 2011). The concept of urbanization economies is in line with the writings of Jacobs (1969), who described the role of diversity in spatial economies.

To deal with the effect of agglomeration economies on productivity growth, this thesis focuses on the terms for externalities proposed by Glaeser et al. (1992), namely Marshall-Arrow-Romer (MAR) externalities (or specialization), Jacobs' externalities (or diversity), and Porter's externalities (or competition). Regarding knowledge spillovers between firms, the notion of Porter's externalities agree with MAR's theory that specialization is better than diversity, so that geographically concentrated industries stimulate growth. However, with regard to the promotion of innovation, Porter's externalities agree with Jacobs' theory, where variety and diversity of geographically proximate industries creates more value than geographical specialization.

Most empirical work on agglomeration economies and productivity uses labour productivity as the main variable to represent productivity levels. However, productivity in this study is represented by the total factor productivity (TFP) growth, which is measured at the firm level. As a measure of productivity, TFP is estimated by considering all inputs used in the production process. Using TFP growth, the analysis in this thesis is expected to provide a broader perspective on productivity, specifically with regard to agglomeration economies.

7.3. Empirical Model

Following the previous research on agglomeration, such as Henderson (2003), Kuncoro (2009), and Lee et al. (2010), the empirical model for testing the effect of agglomeration economies on productivity growth can be specified as:

$$TFP_{ijt}=\alpha_0+AGG_{jt}^{'}\beta_1+Z_{it}^{'}\beta_2+D_j^{'}\beta_3+\varepsilon_{ijt} \qquad (7.1)$$

where TFP_{ijt} is a measure of productivity for firm *i* in region *j* at time *t*, which is represented by a firm's productivity growth. Productivity growth in this study is estimated using the Färe-Primont productivity index, following O'Donnell (2012).[19] AGG_{jt} are agglomeration economies variables of region *j* at time *t*, such that AGG consists of LQ (MAR externalities or specialization), DIV (Jacobs' externalities or diversity), and COM (Porter's externalities or competition). Z_{it} are firm and industry characteristics that include firm age (AGE), firm size (SIZE), and industrial concentration (CR4), while D_j is a dummy variable representing urban area (DURB). The parameters to be estimated are β_1, β_2, and β_3. Finally, ε_{ijt} represents the error term.

If there are unobservable effects such as of region or industry, the error term structure in the above model is:

$$\varepsilon_{ijt}=v_j+\mu_{ijt} \tag{7.2}$$

where v_j represents the region or industry fixed effects. Without controlling for fixed effects, the estimation of agglomeration variables in Equation (7.1) is biased whenever those error terms in Equation (7.2) are correlated with the observed variable. Since the agglomeration economies variables are measured at regional levels, dummy variables are included, just as a dummy variable used for urban regions above.

7.4. Estimation Method

7.4.1. Static Model

The empirical model in Equation (7.1) is estimated using a panel data framework. Henderson (2003) is the first researcher to apply this method using firm-level data in order to estimate the effect of externalities on productivity growth. He argues that panel data allow us to deal with some of the selectivity issues that are uncovered in cross-section models, and may help in dealing with endogeneity problems. By using panel data in this case, it is possible to explore a variety of hypotheses regarding the nature of these externalities, including whether the nature of local scale externalities derives from information spillovers, interaction in labour markets, or local-industry specialization.

The use of the panel data method provides some advantages in estimation. In panel data, heterogeneity can explicitly be taken into account by allowing for subject-

[19] The details of the method used to measure firm-levels productivity are presented in Appendix 7.1.

specific variables. Panel data also provide more informative data, are better suited to study the dynamics of change, enable the study of more complicated behavioural models, and can minimize bias resulting from the aggregation of individuals' or firms' data (Gujarati and Porter 2009).

To estimate the model in Equation (7.1), this study starts with the pooled ordinary least square (pooled-OLS) model, followed by the fixed effects within-group (FEM within) and random effects model (REM). To determine whether the fixed effects model (FEM) or the random effects model (REM) is appropriate given the panel dataset available, a Hausman test is performed. This test determines whether the composite error term is correlated with the explanatory variables; that is, whether the error component model (ECM) or REM is the appropriate model. This procedure can also be performed using the Breusch-Pagan (BP) method to test the hypothesis that there are no random effects, or by a Hausman test for a fixed effects model (Gujarati and Porter 2009).

7.4.2. Dynamic Model

Following previous studies, like Bosma et al. (2008) and Andersoon and Lööf (2012), we run Equation (7.1) using a dynamic model in order to check whether serious endogeneity exists. Another reason why a panel dynamic model is necessary to employ in this case is that the structure of the data includes spatial observations, where temporal correlations of variables used in the model have likely occurred. The commonly used approach is the dynamic panel data estimation technique developed by Arrelano and Bond (1991) and Blundell and Bond (1998), in which the former is recognized as the difference generalized method of moments (GMM-DIF) while the latter is called the system generalized method of moments (GMM-SYS). In brief, the panel dynamic model is intended to improve the fixed effects model, since its estimation results tend to be biased specifically toward short panels, i.e. few time periods and large number of cross-section observations (Ciochini 2006). For short panels, GMM-SYS is better than GMM-DIF, especially in terms of precision and small sample bias. An additional advantage of GMM-SYS over GMM-DIF is that it is still possible to include time-invariant covariates in the model such as a dummy variable (Blundell and Bond 1998). Based on Equation (7.1), the general equation for the dynamic model can be written as:

$$TFP_{ijt}=\gamma_1 TFP_{ijt-1}+\ldots+\gamma_p TFP_{ijt-p}+AGG'_{jt}\beta_1+Z'_{it}\beta_2+D'_j\beta_3+\alpha_i+\varepsilon_{ijt} \quad (7.3)$$

Equation 7.3 considers an autoregressive model of order p in TFP_{ijt} [an AR(p) model] with $TFP_{ijt-1}+\ldots+TFP_{ijt-p}$ as covariates, as well as other independent variables in the model. α_i represents fixed effects, and the goal is to consistently estimate $\gamma_1,\ldots,\gamma_p$ and β.

Like all linear GMM estimators, both GMM-DIF and GMM-SYS can be estimated using one- or two-step procedures. The one-step procedure uses a 2SLS estimator. Since the model is overidentified, more efficient estimation can be performed using the optimal generalized method of moments (GMM) framework, which is also called a two-step estimator, because the optimal weighting matrix is obtained in the first step and used in the second-step (Cameron and Trivedi 2010). The GMM-SYS technique is suitable for short panel data or panel data with few time observations. However, if the number of time periods increases, the GMM-SYS becomes less useful as the number of instruments increases exponentially (Roodman 2009). This research uses a time period of 10 years, which is particularly low relative to the number of firms. Thus, the data are more suitable for this type of GMM panel data analysis. To obtain robust estimation results, we also apply an alternative approach, the two-step procedure and finite sample correction proposed by Windmeijer (2005).

7.5. Data and Measurement Variables

The data used in this analysis are provided by the Statistics Indonesia (*Badan Pusat Statistik – BPS*), as explained in Chapter 5. All independent variables used in the estimation, including LQ (specialization), DIV (diversity), COM (competition), AGE (firm age), SIZE (firm size), CR4 (concentration industry) and DURB (dummy for urban area) have also been explained in Chapter 5. The dependent variable, total factor productivity (TFP) growth, is measured using the Färe-Primont productivity index proposed by O'Donnell (2012) and estimated from firm-level data. A detailed discussion of the method is presented in Appendix 7.1. The estimation of Equations (7.1) and (7.3) is performed for the period from 2000 to 2009. Since a large number of capital values are missing, specifically within the period form 2000 to 2003, to obtain a sufficient number of observations this study applies a back-casting method to estimate the missing values. This method has been used in previous studies such as Vial (2006), Ikhsan (2007), and Suyanto et al. (2009). The detailed method is presented in Appendix 7.2. In addition, the approach used to create a balance panel data set is the same as the method used in Chapter 5.

7.6. Analysis of Empirical Results

7.6.1. Estimation Approach

This section analyses the empirical findings from the estimation of Equation (7.1). Table 7.1 presents the estimation results of four different models. The first model (1) is the pooled OLS or population-average model or common effects. The second model (2) employs an assumption of random-effects using the generalized least squares (GLS) model (REM). The third model (3) is the fixed effects within transformation model (FEM within), while the fourth (4) uses Driscoll and Kraay (1998) standard errors for coefficients estimated by fixed effects (within) regression (FEM D-K).

To choose the appropriate model, either fixed effects or random effects, the Hausman test is employed. The overall statistic, $\chi^2(7)$, has ρ = 0.000. This leads to strong rejection of the null hypothesis that individual effects are random, meaning that only the fixed effects model can provide consistent estimates. To overcome heteroskedastic problems, the estimation of the standard error in the FEM (within) model is adjusted to the cluster-robust inference method.[20] However, if autocorrelation is present, this approach cannot work optimally. Thus, the estimation result is still inconsistent and biased. Since autocorrelation is regarded as a nuisance in the residuals, it needs to be corrected.

[20] The estimation of panel data models is usually based on the assumption of the idiosyncratic error $\varepsilon_{it} \sim (0, \sigma_\varepsilon^2)$. In fact, this assumption is often not satisfied in application. In this case, many panel estimators still retain consistency, provided that ε_{it} are independent over i, but reported standard errors are incorrect. In a short panel (few T and large N), cluster-robust standard errors can be obtained under the assumption that errors are independent across N and that $N \to \infty$. Specifically, $E(\varepsilon_{it}\varepsilon_{js}) = 0 \; for \; i \neq j$, $E(\varepsilon_{it}\varepsilon_{js})$ is unrestricted, and ε_{it} may be heteroskedastic. The approach leads to a cluster-robust estimate of the variance-covariance matrix of the estimator (VCE) (see Cameron and Trivedi 2010).

Table 7.1: The Effect of Agglomeration Economies on TFP Growth 2001–2009

Independent variables	Pooled OLS	REM	FEM (within)	FEM (D-K)
	(1)	(2)	(3)	(4)
LQ *(specialization)*	10.948	10.948	24.172	24.172
	(7.69)[a)]	(7.90)[a)]	(13.00)[a)]	(5.21)[a)]
DIV *(diversity)*	-1.954	-1.954	-4.737	-4.737
	(-14.60)[a)]	(-12.64)[a)]	(-17.54)[a)]	(-5.94)[a)]
COM *(competition)*	1.622	1.622	-0.598	-0.598
	(0.80)	(0.77)	(-0.24)	(-0.08)
AGE *(firm's age)*	-0.160	-0.160	-0.277	-0.277
	(-7.96)[a)]	(-7.37)[a)]	(-5.53)[a)]	(-2.38)[b)]
SIZE *(firm's size)*	19.194	19.194	32.609	32.609
	(59.51)[a)]	(62.52)[a)]	(73.83)[a)]	(5.71)[a)]
CR4 *(concentration)*	-0.055	-0.055	-0.524	-0.524
	(-3.78)[a)]	(-4.00)[a)]	(-16.28)[a)]	(-4.65)[a)]
DURB *(dummy urban)*	7.488	7.488	20.413	20.413
	(14.71)[a)]	(12.43)[a)]	(19.81)[a)]	(5.03)[a)]
Constanta	-64.511	-64.511	-104.253	-104.253
	(-23.39)[a)]	(-23.67)[a)]	(-26.65)[a)]	(-4.71)[a)]
N	4,516	4,516	4,516	4,516
Observations	40,644	40,644	40,644	40,644
R^2	0.1926	0.1926	0.1857	0.3258
Hausman test for FEM: Probability (χ^2) = 0.000 → FEM				
Serial correlation (Wooldridge test)			Prob(χ^2) = 0.000	
Heteroskedastic (modified Wald test)			Prob(χ^2) = 0.000	

Note: t-statistics are in the parenthesis; [a)], [b)], and [c)] denote 1%, 5% and 10% significance level, respectively.

The test result for the detection of autocorrelation and heteroskedasticity in Table 7.1 shows that model 3 (FEM-within) suffers from both problems. To deal with this situation, we apply the Driscoll and Kraay (1998) standard errors for coefficients estimated by pooled OLS/WLS or fixed effects (within) regression. In this method, the error structure is assumed to be heteroskedastic, autocorrelated up to some lags, and possibly correlated between the groups (panels). These standard errors are robust to general forms of cross-sectional (spatial) and temporal dependence when the time dimension becomes large.[21] Model 4 in Table 7.1 presents the results of the estimation using the Driscoll and Kraay (1998) approach to address the problem of autocorrelated and heteroskedastic errors in panel data.

[21] For a detailed approach, see STATA online resources (www.stata.com).

The coefficients of models 3 and 4 are exactly the same. Both models are estimated using fixed effects (within) approach. However, there is a substantial change in the standard error of estimation as a result of nuisance correction in the residuals. The estimation of the four models is presented in Table 7.1. Model 4 is recognized as the most appropriate approach, and the results will be used in explaining the effect of agglomeration economies and industrial characteristics on firm productivity growth.

Before continuing to the discussion of the estimation results, another common approach is also used to eliminate the autocorrelation problem in the static panel data. This is done by applying first-order autoregression (AR1), where the residuals become:

$$\varepsilon_{it}=\rho\varepsilon_{i,t-1}+\omega_{it} \tag{7.4}$$

where ω_{it} are independent and identically distributed *(iid)* with zero mean and ρ is the autocorrelation parameter whose absolute value is less than one. The test for autocorrelation can be performed, for example, by the modified Durbon-Watson test for first–order serial correlation proposed by Baltagi and Wu (1999). The presence of autocorrelation in the autoregression on lagged variables can indicate the need for dynamic panel data analysis (Greene 2003).

The estimation of AR1 in Equation (7.4) is performed using the feasible generalized least square (FGLS) procedure. This procedure first estimates the basic model in Equation (7.1) using OLS and then uses the residual from this estimation to estimate ρ in Equation (7.4) (Comeron and Trivedi 2010). The estimation results for the AR1 model are consistent with the Driscoll and Kraay (1998) approach (Model 4), indicating that the model is valid.[22] The Baltagi-WU LBI score is 2.139, indicating no serious autocorrelation.

7.6.2. Agglomeration Economies Variables

A number of interesting findings from Table 7.1 are analysed in the following discussion. The analysis starts with the impact of agglomeration economies on productivity growth with regard to the specialization (LQ) and diversity (DIV)

[22] The detailed estimation result for the fixed-effects model with AR1 is presented in the Appendix 7.3.

variables. The results show a positive effect of specialization on productivity growth, while diversity has an opposite direction or negative effect on productivity growth.

The findings confirm Marshall's (1920) theory of agglomeration, in which knowledge and information spillovers among firms, as well as inter-industry backward-forward linkages, are effectively exchanged and transmitted in the regions that consist of homogenous industries. Specialization also encourages the exchange of product development ideas, whether tacit or explicit, through different mechanisms such as imitation, business interactions, and inter-firm movement of skilled labour, without additional transaction costs (Sanexian 1994). The results also suggest that spatial proximity favours the intra-industry transmission of knowledge. In specialized regions, specifically those with larger labour pools, it is easier for people to learn from each other. The absorption of different experiences from people with similar competencies contributes to the acceleration of skill acquisition and thus to higher productivity (Beaudry and Schiffauerova 2009).

Empirical studies of the effect of agglomeration economies on firm productivity growth have found mixed results. In the case of Indonesia, these findings are in accordance with those of Kuncoro (2009) and the World Bank (2012). Using real value added per worker to proxy firm-level productivity, Kuncoro (2009) investigates the effects of localization and urbanization economies for selected manufacturing industries from 1990 to 2003. In general, the findings show that the forces of localization are stronger than the forces of urbanization for stimulating productivity levels. The presence of localization implies that small regions tend to specialize in specific industries or similar connected industries. Accordingly, using an approach similar to Kuncoro's (2009), World Bank (2012) reports a finding of a positive effect of agglomeration economies on firm-productivity levels in selected Indonesian manufacturing industries. Firms located in agglomeration areas enjoy a higher total factor productivity growth than those that are located outside agglomeration areas. This indicates that agglomeration has a positive correlation with firm performance, even though it does not prove the causal relationship between location in agglomeration areas and firm-level productivity.

The findings of this thesis are also in line with the previous investigation of agglomeration economies on firm productivity in international cases. The evidence that firm productivity benefits from higher degrees of specialization of industry environments is affirmed in other similar studies. For example, Henderson et al. (2001) find a positive influence of agglomeration on labour productivity in the Korean manufacturing industry. Focusing on the number of plants in the same industry as source of spillovers effects, Henderson (2003) finds similar evidence for selected manufacturing industries in the United States. Graham and Kim (2008) confirm positive elasticities of production with respect to agglomeration in manufacturing industries in the United Kingdom. More recently, Andersoon and Lööf (2011) report a positive effect of agglomeration upon labour productivity in Swedish manufacturing industries. Similar findings occur in other studies, such as Harrison et al. (1996) for the U.S manufacturing industry, Deckle (2002) for Japanese prefectures, Capello (2002) for the Italian manufacturing industry, de Lucio et al. (2002) in Spain's manufacturing industry, and Cingano and Schivardi (2004) for local Italian industries.

The third agglomeration economy variable is competition (or Porters' externalities). Its effect on productivity growth is negative but not significant, implying that for the aggregated manufacturing industry, competition does not significantly affect firm productivity growth. This result differs from the positive effect of competition on firm-level technical efficiency, as discussed in Chapter 5. Although competition has a positive effect on firm-level technical efficiency, its effect on productivity growth is uncertain. However, the analysis at the two-digit industry level in the following sub-section shows a different insight, in that competition exerts a significant influence on productivity growth for particular industries.

7.6.3. Firm and Industry Characteristics

Moving to the effects of firm and industry characteristics on productivity growth, Table 7.1 provides estimation results for firm age, size, and market concentration. Firm age (AGE) has a negative effect on productivity growth, meaning that older firms tend to have lower productivity, while younger firms tend to have higher productivity. In this regard, Teece (1986) and Winter (1987) argue that younger firms have advantages in the area of knowledge, and the use of modern technology and sophisticated machinery. Moreover, younger firms tend to give more attention to research and development (R&D). Accordingly, Pitt and Lee (1981) state that younger firms can adopt the most efficient technology available when they initially begin production. These conditions allow the younger firms to achieve higher productivity than older firms. In Indonesia's case, this finding supports the studies of Pitt and Lee (1981), Hill and Kalirajan (1993), and Suyanto et al. (2009). The effect of age on firm productivity growth, however, remains controversial. Other scholars argue that older firms should have higher productivity because they tend to have more experience than younger firms, and are able to run their operations more efficiently. Older firms also have more experience in management issues and surviving in unfavourable economic conditions (Arrow 1962). With more experience in the production process, older firms have greater "know-how" about internal management (Lecraw 1978).

In addition, firm size (SIZE) has a positive effect on productivity growth. This suggests that larger firms tend to be more productive than smaller firms. This is not surprising, since large firms, in general, have large market shares that lead to stronger market power relative to small firms. Large firms tend to have better market access and more professional management, and are faster in responding to changes in the business environment. These advantages allow large firms to achieve higher productivity growth than small firms. This finding is similar to the findings of previous research such as Pitt and Lee's (1981) on the Indonesian weaving industry. Bhandari and Ray (2012) find similar results for the Indian textile industry; Fan and Scott (2003) for furniture and plastic products in Chinese industries; Cingano and Schivardi (2004) for Italian manufacturing industries; and Kalkulis (2010) for the semi-conductor and pharmaceutical industries in the U.S.

The third variable representing firm and industry characteristics is industrial concentration (CR4), which represents the level of concentration in each industry sub-sector. The estimation results in Table 7.1 show that CR4 has a negative effect on productivity growth, meaning that higher market concentration levels or industries with oligopolistic market structures tend to reduce firm productivity growth. This also means that oligopolistic or monopolistic market structures do not offer environments favourable to the stimulation of firm productivity. In an oligopolistic structure, the incumbents will set the market conditions and try to deter new competitors from entering the market. This condition leads to low incentives for companies to innovate, and hence in turn to slow productivity growth. In the case of Indonesia, this result is in line with the findings of Setiawan et al. (2012). They find a negative relation between industrial concentration and efficiency level in Indonesian food and beverage industries at the 5-digit ISIC level for the period from 1995 to 2006.

Finally, the estimation includes a dummy variable representing urban region to capture the influence of firm location on productivity growth. Location choice plays an important role in stimulating firm performance, more specifically in a country like Indonesia, where large regional disparities exist. The findings in Table 7.1 show positive effects of urban regions (DURB) on productivity growth, indicating that firms located in urban areas tend to have higher productivity relative to firms located outside urban areas. This result is expected, as urban areas are more developed than non-urban areas and serviced by better infrastructure. In addition, most urban areas are located near centres of agglomeration such as Jakarta (the capital of Indonesia), Surabaya (the capital of East Java province), Bandung (the capital of West Java province), Semarang (the capital of Central Java province) and Batam (the island location of the special economic zone). In this regard, the World Bank (2012) reports that firms located in agglomeration areas enjoy higher productivity relative to those located outside agglomeration areas, and the productivity gap between firms located in the two different regions increases over time.

The positive effects of urban area on productivity growth also indicate that the presence of a sound business environment is key to the improvement and acceleration of productivity growth. According to the World Bank (2012), the supporting environment may capture governance, infrastructure, service industries, the local labour market, and the regulatory environment. Conceptually, urban areas should be conducive to industrial agglomeration due to regional advantages, home market effects, and consumption levels. The home market effect assumes that locations with larger local demand will attract a disproportionate share of firms in imperfectly competitive industries (Ottaviano and Thisse 2004).

7.6.4. Analysis by Industry

This sub-section discusses the effect of agglomeration economies upon productivity growth at the two-digit industry level. The estimation results by two-digit industry are presented in Table 7.2. As with the estimations for the aggregated manufacturing industry, estimation at the two-digit industry level is also performed using the autoregression (AR1) method, as explained in sub-section 7.6.1. The analysis of agglomeration economies by two-digit manufacturing industry is intended to allow the observation of the effect of agglomeration economies on productivity growth in deeper industrial sectors. A broader feature of the relationship between agglomeration economies and productivity growth is expected to be found in this analysis. Since each industry sub-sector has specific characteristic and a specific structure, it is possible to determine the differing effects of agglomeration economies on productivity growth. Most empirical studies of agglomeration economies and productivity, such those of Henderson (2003), Kuncoro (2009), and Andersoon and Lööf (2012), are performed by selecting particular industries.

In general, the empirical findings by industry sub-sector in Table 7.2 are in accordance with the results for the aggregated industry in Table 7.1. Specialization (or MAR externalities) has a significant positive effect on productivity growth for all two-digit manufacturing industries, except for the wood and wood products industry (ISIC 20) and the medical, precision, and optical instruments industry (ISIC 33), in which the effect is positive but not significant. In addition, diversity (or Jacobs' externalities) negatively affects almost all manufacturing sectors except for the wood and wood products industry (ISIC 20) and the basic metals industry (ISIC 27). As discussed in the previous sub-section, these findings suggest that at the two-digit industry level, specialization is also more favourable for stimulating productivity growth than diversity. The empirical results for two-digit manufacturing sectors support the findings for the aggregated manufacturing industry, implying that the nature of specialization is thoroughly consistent in manufacturing industries.

Moving to the effect that competition (or Porter's externalities) exerts on productivity growth, the findings for two-digit industry sub-sectors in Table 7.2 are different from the findings for the aggregated industry in Table 7.1. A positive effect of competition on productivity growth is found in several manufacturing industries including the textiles industry (ISIC 17), paper and paper products industry (ISIC 21), publishing and printing industry (ISIC 22), coal, petroleum, and nuclear industry (ISIC 23), chemicals and chemical products industry (ISIC 24), rubber and plastic products industry (ISIC 25), and furniture industry (ISIC 36). These results support Porter's (1990) argument that competition is suitable for stimulating firm productivity. A competitive region or market provides substantial incentives for firms to innovate, which then improves the efficiency and productivity level.

However, competition has a negative effect on productivity growth in the tobacco industry (ISIC 16), implying that an oligopolistic or monopolistic structure would be a condition that would improve productivity in this industry. This result also suggests the existence of MAR externalities. The tobacco industry is highly concentrated, only exists in certain regions, is dominated by a very limited number of firms, and the average market concentration reaches 60 percent. This industry structure may lead an oligopolistic market to be more suitable for stimulating productivity growth in the tobacco industry.

In addition, regarding the effect of firm and industry characteristics on productivity growth, the estimation results show that firm age (AGE) has a negative effect for the majority of the industries at the two-digit level. In general, the findings at the two-digit industry level are in line with the finding about the aggregate industry presented in Table 7.1. As discussed in the previous sub-section, the negative effect of age suggests that younger firms tend to have higher productivity growth than older firms. However, some industries show positive effect of age on productivity growth, such as the apparel industry (ISIC 18), other non-metallic mineral products industry (ISIC 26), medical, precision, and optical instruments industry (ISIC 33), furniture industry (ISIC 36), and recycling industry (ISIC 37). These findings indicate that older firms in these industries tend to have higher productivity than younger firms.

As discussed in the previous sub-section, the effect of age on productivity growth in a particular industry can be positive or negative depending on the characteristics, structure, and conduct of the industry. As argued by Arrow (1962), older firms can enjoy higher productivity because they have more learning experience than younger firms and thus can run their operation more efficiently, leading to more efficient production. Older firms have experience in handling management issues and surviving in unfavourable economic conditions.

Table 7.2: The Effect of Agglomeration Economies and Firm Characteristics on TFP Growth at 2-Digit ISIC 2001-2009[23]

Independent variables	ISIC 15	ISIC 16	ISIC 17	ISIC 18	ISIC 19	ISIC 20	ISIC 21	ISIC 22	ISIC 23	ISIC 24	ISIC 25
LQ *(specialization)*	11.44	89.42	35.04	37.95	65.52	6.24	72.35	14.69	80.03	16.97	52.73
	(2.57)a)	(6.57) a)	(5.44) a)	(4.88) a)	(4.75) a)	(0.56)	(4.93) a)	(1.95) b)	(2.24) b)	(2.93) a)	(9.68) a)
DIV *(diversity)*	-1.30	-9.97	-8.61	-5.05	-5.20	0.12	-8.74	-6.91	-2.58	-2.48	-1.91
	(-2.75) a)	(-6.81) a)	(-8.84) a)	(-3.70) a)	(-2.37) b)	(0.11)	(-4.56) a)	(-5.07) a)	(-0.48)	(-2.36) b)	(-2.18) b)
COM *(competition)*	-1.58	-68.81	26.44	2.68	1.85	-0.36	61.92	44.46	203.32	32.18	16.60
	(-0.34)	(-5.79) a)	(3.17) a)	(0.25)	(0.09)	(-0.03)	(3.29) a)	(3.36) a)	(3.44) a)	(3.02) a)	(1.88) b)
AGE *(firm's age)*	-0.03	-0.29	-0.30	0.68	-0.04	0.06	-0.75	-0.67	-12.29	-0.72	-0.54
	(-0.53)	(-2.00) b)	(-2.63) a)	(4.06) a)	(-0.14)	(0.31)	(-2.75) a)	(-3.24) a)	(-4.86) a)	(-4.68) a)	(-4.90) a)
SIZE *(firm's size)*	39.14	36.46	31.26	28.53	39.72	31.87	26.04	41.44	74.37	40.76	31.67
	(59.24) a)	(19.89) a)	(30.22) a)	(20.92) a)	(14.98) a)	(19.72) a)	(10.41) a)	(20.79) a)	(8.54) a)	(26.83) a)	(28.58) a)
CR4 *(concentration)*	-1.70	0.19	-1.32	-0.88	-0.73	0.77	-0.35	0.32	-0.29	-0.58	1.42
	(-13.72) a)	(0.91)	(-7.97) a)	(-5.64) a)	(-3.42) a)	(2.32) b)	(-1.16)	(2.08) b)	(-0.66)	(-7.07) a)	(4.52) a)
Constanta	-92.30	-70.45	-73.63	-90.59	-119.25	-137.26	-118.94	-130.94	-385.94	-125.80	-164.93
	(-15.80) a)	(-3.00) a)	(-5.95) a)	(-6.12) a)	(-4.94) a)	(-8.34) a)	(-3.81) a)	(-7.35) a)	(-4.08) a)	(-9.20) a)	(-13.30) a)
N	1,148	151	476	213	88	212	105	117	6	273	429
Observations	9,184	1,208	3,808	1,704	704	1,696	840	936	48	2,184	3432
R^2	0.1927	0.1812	0.1731	0.1458	0.1534	0.1509	0.1283	0.2180	0.2926	0.1725	0.1561
Modified Bhargava DW	2.17	1.89	2.04	2.09	2.15	2.03	2.05	2.11	1.95	2.17	2.08

Note: t-statistics are listed in parentheses; a), b), and c) denote 1%, 5%, and 10% significance level, respectively.

[23] The estimation results in this table derive from the fixed-effects model, with correction for autocorrelation using AR1 ($\varepsilon_{i,t-1}$). Variable DURB (dummy for urban region) is omitted, because at 2-digit ISIC levels, several industries contain firms that are located only in urban regions or only in non-urban regions.

Table 7.2: (continued...)

Independent variables	ISIC 26	ISIC 27	ISIC 28	ISIC 29	ISIC 31	ISIC 32	ISIC 33	ISIC 34	ISIC 35	ISIC 36	ISIC 37
LQ *(specialization)*	68.39	21.71	47.48	55.22	37.30	111.46	20.92	30.93	23.61	43.46	45.98
	(13.23) [a)]	(1.95) [c)]	(6.83) [a)]	(4.68) [a)]	(2.77) [a)]	(2.24) [b)]	(0.61)	(2.26) [b)]	(2.25) [b)]	(5.91) [a)]	(2.12) [b)]
DIV *(diversity)*	-4.01	1.51	-6.53	-6.17	-4.20	-6.99	-7.67	-9.76	-1.43	-5.71	-4.72
	(-4.57) [a)]	(0.46)	(-5.48) [a)]	(-3.50) [a)]	(-1.80) [c)]	(-1.53)	(-1.75) [c)]	(-4.71) [a)]	(-0.91)	(-5.78) [a)]	(-1.60)
COM *(competition)*	-3.20	-21.81	-9.71	-29.96	-45.05	29.63	31.84	-25.84	15.82	47.97	48.67
	(-0.39)	(-0.81)	(-0.77)	(-1.36)	(-1.46)	(0.43)	(0.59)	(-1.12)	(0.96)	(4.66) [a)]	(1.35)
AGE *(firm's age)*	0.26	-1.54	-0.13	-0.23	0.25	-1.27	1.42	-0.02	-0.77	0.33	0.92
	(2.23) [b)]	(-2.62) [a)]	(-0.59)	(-0.79)	(0.67)	(-1.15)	(1.68) [c)]	(-0.07)	(-2.10) [b)]	(1.79) [c)]	(1.75) [c)]
SIZE *(firm's size)*	43.28	34.83	41.65	43.73	52.04	55.79	45.36	28.10	38.17	40.01	45.23
	(36.88) [a)]	(9.46) [a)]	(23.86) [a)]	(17.58) [a)]	(14.39) [a)]	(8.60) [a)]	(5.99) [a)]	(10.65) [a)]	(13.31) [a)]	(30.93) [a)]	(6.75) [a)]
CR4 *(concentration)*	-0.70	-4.01	0.00	-0.55	-1.69	1.06	-0.95	-0.55	0.89	-1.17	0.11
	(-4.52) [a)]	(-5.68) [a)]	(0.02)	(-1.91) [c)]	(-4.09) [a)]	(1.89) [c)]	(-1.00)	(-1.46)	(2.65) [a)]	(-6.18) [a)]	(0.68)
Constanta	-146.00	0.53	-117.39	-92.80	-90.19	-238.24	-146.35	0.44	-193.31	-161.72	-155.64
	(-11.20) [a)]	(0.01)	(-8.03) [a)]	(-3.63) [a)]	(-2.80) [a)]	(-2.85) [a)]	(-1.69) [c)]	(0.01)	(-5.67) [a)]	(-12.52) [a)]	(-3.76) [a)]
N	389	54	182	84	60	15	15	70	67	243	19
Observations	3112	432	1,456	672	480	120	120	560	536	2,744	152
R^2	0.2346	0.1863	0.1994	0.2146	0.1612	0.2042	0.1546	0.1668	0.1756	0.1775	0.1771
Modified Bhargava DW	2.08	2.21	2.13	2.19	2.16	2.20	2.02	2.00	2.08	2.08	2.24

Note: t-statistics are in parentheses; [a]), [b]), and [c]) denote 1%, 5%, and 10% significance level, respectively.

ISIC 15: Food products and beverages; ISIC 16: Tobacco; ISIC 17: Textiles; ISIC 18: Apparel; ISIC 19: Tanning and dressing of leather; ISIC 20: wood and wood products; ISIC 21: Paper and paper products; ISIC 22: Publishing and printing; ISIC 23: Coal, petroleum, and nuclear; ISIC 24: Chemicals and chemical products; ISIC 25: Rubber and plastics products; ISIC 26: Other non-metallic mineral products; ISIC 27: Basic metals; ISIC 28: Fabricated metal products; ISIC 29: Machinery and equipment n.e.c; ISIC 31: Electrical machinery and apparatus n.e.c; ISIC 32: Radio, television, and communication; ISIC 33: Medical, precision, and optical instruments; ISIC 34: Motor vehicles; ISIC 35: Other transport equipment; ISIC 36: Furniture; ISIC 37: Recycling.

Furthermore, the effect of firm size (SIZE) on productivity growth is positive for all two-digit industry sub-sectors, which confirms the results of the aggregate samples of industries in Table 7.1. The results indicate that the tendency of large firms to have higher productivity than small firms occurs in all industries levels. Finally, industrial concentration (CR4) shows negative effect on productivity growth in almost all two-digit industry sub-sectors. In line with the findings in Table 7.1, these results prove that a competitive market is better for stimulating firm productivity, since it provides incentives for firms to innovate. Higher innovation levels lead to faster productivity growth.

7.6.5. Dynamic Model

Before analysing the results, some estimation issues of the dynamic model will be discussed first. The estimation of the dynamic model uses real labour productivity as the dependent variable instead of total factor productivity growth. In this case, labour productivity is measured by the value of real output divided by the total labour. This measurement is used because dynamic panel data such as GMM-SYS requires the variables in difference-value form for estimation, so applying total factor productivity growth as the dependent variable produces complicated data, because the value of TFP growth is already included in the difference. As a result, the estimation of dynamic model requires level data. In comparing outcomes to previous studies such as those by Henderson (2003), Kuncoro (2009), the World Bank (2012) and Andersoon and Lööf (2011), the total factor productivity growth in the dynamic model is replaced by real labour productivity. However, for the purpose of discussion, the estimation results of the effect of agglomeration economies on productivity growth using TFP growth as the dependent variable are presented in Appendix 7.4.

Table 7.3 presents the estimation results of the effect of agglomeration economies on productivity using a dynamic model. The data used for this estimation is for the period from 2000 to 2009. The time period for the dynamic model is longer than in the static model, but with fewer observations, because the lag structure in the dynamic model must be considered. The first column of Table 7.3 shows the results when using pooled-OLS, while the second column displays the results for the fixed-effect model. The estimation results for the dynamic model using the GMM-SYS approach are presented in the third and fourth column. The difference between the two models is that the fourth model includes the square value of firm age (AGE) and market concentration (CR4). These variables are included in order to obtain the quadratic relationship of those variables with productivity.

Hsiao (2002), explains that the estimation of a dynamic panel model using pooled-OLS with a single lag in dependent variable tends to be biased upwards if an individual-specific effect is present. Conversely, estimation using fixed effects (FE) is biased downward if the panel data is short (Nickell 1981). Under this condition, GMM-SYS can offer an unbiased or consistent estimation of a lagged dependent variable, since its estimation lies on the interval of the pooled-OLS and the FE model (Bond et al. 2001; Roodman 2009).

The GMM-SYS in column Table 7.3 is performed using a two-step procedure and finite sample correction following Windmeijer (2005), with a robust variance-covariance estimator.[24] The coefficient of the lag of productivity or TFP(-1) for the GMM-SYS model lies on the interval of the pooled-OLS and FE models, indicating unbiased or consistent estimation. The positive effect of the lag of productivity suggests that previous firm productivity induces current productivity levels. Since productivity is influenced by technological progress, the finding indicates that firm productivity also depend on the level of technology used by the firm in an earlier period.

The estimation results for agglomeration economies using the dynamic model in Table 7.3 are in accordance with the results of the static model presented in Table 7.1, in which specialization (or MAR externalities) and diversity (or Jacobs' externalities) have respectively positive and negative effects on productivity growth. In addition, the findings about firm and industry characteristic variables show mixed results. In column 3 of Table 7.3, firm age (AGE) and market concentration (CR4) have positive effects on productivity, which is opposite to the results of the static model in Table 7.1. The positive sign of AGE means that older firms tend to have higher productivity than younger firms, while the positive sign of CR4 indicates that a oligopolistic or monopolistic market structure is more appropriate for improving productivity than a competitive market.

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[24] The estimation is performed using Stata 12.1 and the command is *xtdpdsys*.

Table 7.3: Estimation Results of the Dynamic Model, Dependent Variable: Labour Productivity 2000–2009

Independent variables	Pooled-OLS (1)	FEM (2)	GMM-SYS (two-step) (3)	GMM-SYS (two-step) (4)
TFP (-1)	0.384	0.087	0.116	0.110
	(90.52)[a)]	(17.77) [a)]	(10.14) [a)]	(9.68) [a)]
LQ *(specialization)*	0.567	0.422	0.375	0.288
	(19.61) [a)]	(12.97) [a)]	(3.07) [a)]	(2.34) [b)]
DIV *(diversity)*	-0.083	-0.054	-0.069	-0.081
	(-25.04) [a)]	(-11.30) [a)]	(-4.73) [a)]	(-5.26) [a)]
COM *(competition)*	0.254	0.128	0.183	0.159
	(5.80) [a)]	(2.75) [a)]	(1.40)	(1.24)
AGE *(firm's age)*	-0.001	0.002	0.011	0.021
	(-1.46)	(2.47) [b)]	(5.36) [a)]	(4.31) [a)]
SIZE *(firm's size)*	0.323	0.395	0.416	0.393
	(62.84) [a)]	(63.24) [a)]	(17.00) [a)]	(16.45) [a)]
CR4 *(concentration)*	-0.001	0.007	0.004	0.024
	(-4.20) [a)]	(9.54) [a)]	(2.56) [b)]	(6.44) [a)]
DURB *(dummy urban)*	0.388	0.457	0.728	0.772
	(30.94) [a)]	(27.29) [a)]	(14.26) [a)]	(15.00) [a)]
$(AGE)^2$				-0.0003
	-	-	-	(-3.65) [a)]
$(CR4)^2$				-0.0003
	-	-	-	(-6.02) [a)]
Constanta	4.794	7.323	6.524	6.564
	(67.65) [a)]	(86.77) [a)]	(24.08) [a)]	(24.19) [a)]
AR(1)	-	-	-30.30	-30.26
			(0.000)	(0.000)
AR(2)	-	-	-1.72	-1.39
			(0.0538)	(0.163)
Instrumental variables	-	-	121	137
Observations	40,644	40,644	36,128	36,128

Note: t-statistics are in parentheses; [a]), [b]), and [c]) denote 1%, 5%, and 10% significance level, respectively.

However, when adding the square value of firm age (AGE) and industrial concentration (CR4) into the model, the estimation results of both variables for the static and dynamic model are actually quite similar, as can be seen in column 4 of Table 7.3. Both square values of AGE and CR4 have negative effects on firm productivity. In column 4, the estimate of AGE implies that firm productivity increase with firm age until a peak of 35 years and then declines[25]. This also means that, on average, younger firms tend to have higher productivity than older firms,

[25] Based on the estimation results in column 4, Table 7.3, the peak level can be calculated by the formula 0.021/(2x0.0003)=35; see Comeron and Trivedi (2010), pages 250.

since there are larger numbers of firms in the samples that are older than the peak point (35 years). Accordingly, the CR4 estimate implies that firm productivity will increase with the level of market concentration until a peak at 40 percent and then decline. Normally, a market is defined as competitive if the concentration level is below 40 percent. This result clearly indicates that a competitive market structure is more favourable for stimulating firm productivity than an oligopolistic or monopolistic one. Based on these results, it can be briefly concluded that the effect of firm age (AGE) and market concentration (CR4) on firm productivity does not differ between the static model and dynamic model. The two remaining variables in column 4 of Table 7.3—firm size (SIZE) and urban region dummy (DURB)—have positive effects on firm productivity, which is also in line with the findings of the static model in Table 7.1.

7.7. Conclusion

This chapter continues the discussion of the two previous chapters by examining the effects of agglomeration economies on productivity growth in the manufacturing industry from 2000 to 2009. Since agglomeration economies deal with location-specific economies, the analysis of this chapter focuses on three main concepts of externalities, namely specialization (or MAR externalities), diversity (or Jacobs' externalities), and competition (or Porter's externalities). The classical debate among scholars is whether specialization or diversity better promotes firm productivity. A set of firm attributes that influences productivity growth is included in the analysis as well. These variables are firm age (AGE), size (SIZE), industrial concentration (CR4), and the dummy variable representing urban region (DURB). An econometric estimation using panel data, either a static or dynamic model is employed to address the effect agglomeration economies on productivity growth.

The empirical findings show evidence of a positive specialization effect and negative diversity effect, indicating that specialization is more favourable than diversity to the stimulation of productivity growth. This confirms that inter-firm knowledge spillovers are exchanged in regions containing homogenous industries. Firms enjoy the benefits of geographic concentration through economies of scale stemming from labour market pooling and transport cost savings. However, on the aggregate industry level, competition (or Porter's externalities) does not exert a clear effect on productivity growth, since the estimation result is not statistically significant.

Turning to the effects that firm and industry characteristics exert on productivity growth, firm age (AGE) has a negative effect, implying that younger firms tend to enjoy higher productivity growth than older firms. Younger firms are likely to have more advantages in the area of knowledge, and the use of modern technology and sophisticated machinery. Firm size (SIZE) shows a positive effect, indicating that larger firms are more productive than smaller firms. Large firm tends to have better market access and more professional management, and are faster in responding to changes in the business environment. These conditions lead to higher productivity growth. In addition, competitive market structures are perceived to be more appropriate than oligopolistic or monopolistic structures for improving firm productivity growth, as demonstrated by the negative effect that industrial concentration (CR4) exerts on productivity growth. High competition provides incentives to firms to innovate, which turn to accelerates technological progress, and hence productivity levels. Finally, the findings show that location in an urban region (DURB) exerts a positive effect on productivity growth. This confirms that firms located in urban regions experience better productivity growth relative to firms located outside urban region, indicating that a sound business environment is very important in improving and accelerating productivity growth.

Several relevant policy implications arise from the above findings. This thesis finds that agglomeration contributes significantly to productivity growth. Therefore, the Indonesian government should consider prioritizing agglomeration in formulating its spatial industrial policy, specifically by focusing on facilitating the agglomeration process and improving the competitiveness of agglomeration areas. As urban regions are found to promote productivity growth, the government should strive to ensure sound and ever-improving business environments in these areas.

Chapter 8
Conclusion and Policy Implications

8.1. Introduction

The effect of agglomeration economies on firms' productivity has received a great deal of attention from policy makers and researchers in the last decade. Agglomeration economies are associated with location-specific economies. Early studies in this field generally focused on economic growth and used aggregate-level data. In contrast, most recent studies concern on productivity by applying firm-level data.

The classical debate is whether specialization (MAR externalities) or diversity (Jacobs' externalities) better promotes firms' productivity, as well as the question of how competition (Porter's externalities) also contributes to productivity. Empirical research shows mixed results. Identifying the effect of agglomeration economies on productivity is challenging and contentious, since a number of questions about agglomeration economies remain. The debate about industrial and geographic concentration and the scope of agglomeration economies continues.

To examine whether agglomeration economies exert a significant effect on firm productive efficiency and productivity growth in the Indonesian manufacturing industry, this thesis develops two main frameworks of research. A stochastic production frontier is applied to investigate the effect of agglomeration economies on firm productive efficiency, and an econometric model using panel data, including static and dynamic models, is employed to investigate the effects of agglomeration economies on firm productivity growth. Meanwhile, the decomposition of productivity growth is performed by using Färe-Primont productivity index. This analysis is intended to enrich the study by examining potential sources of productivity growth and mapping which industrial sectors experience maximum or minimum productivity levels.

Using total factor productivity (TFP) growth as the measure of productivity is a distinguishing feature of this study. This measure has been rarely used as the productivity measure in research on agglomeration economies. The use of firm-level data has received a great deal of attention in the last decade. However, most empirical research uses real labour productivity to measure firms' productivity levels and is also conducted using aggregate level data. Since agglomeration economies involve micro-level behaviours, the use of firm-level data makes it possible to achieve broader perspectives on agglomeration economies. Agglomeration economies are understood to improve firm productivity because firms benefit by being closely located or regionally proximate, leading to intra-firm knowledge and information spillovers, labour pooling, and reductions of transaction costs. Considering the different characteristics and structures of each industry, this thesis examines the effects of agglomeration economies on productivity growth not only for the aggregated industry but also for the two-digit manufacturing level, which includes 21 industry sub-sectors.

The main contributions of this thesis are as follows. (1) it examines the effect of agglomeration economies on firm-level productive efficiency under the stochastic production frontier framework, which allows the identification of agglomeration economies' effects on firm level technical efficiency. (2) it is one of the first studies on the effect of agglomeration economies in the Indonesian context to use total factor productivity (TFP) growth as the dependent variable. (3) it estimates the effect of agglomeration economies on productivity growth in both the aggregated manufacturing industry and two-digit level industries. (4) it decomposes productivity growth by three-digit level manufacturing industries, which allows the identification of industry sub-sectors that experience maximum or minimum productivity levels.

8.2. Major Findings

This thesis provides empirical analysis of the effect of agglomeration economies on firm level productive efficiency and productivity growth in the Indonesian manufacturing industry. Several interesting findings from this study enrich the research in the field of agglomeration economies. Most of the results match the theory established in the literature and in line with previous studies performed in other countries. However, this study also offers some new perspectives that may be valuable for researchers and specifically for the policy makers in Indonesia, where agglomeration has become a main feature of national industrial development. These findings are summarized in the following sub-section.

8.2.1. The Effect of Agglomeration Economies on Firm-Level Productive Efficiency

The empirical results (Chapter 5) show positive effects of specialization (or MAR externalities) and negative effect of diversity (or Jacobs' externalities) on firm-level productive efficiency. This analysis is performed at the level of aggregated manufacturing industry. The findings support Marshall's theory of agglomeration and indicate that firms located in more specialized regions tend to enjoy higher efficiency than firms located in more diversified regions. Furthermore, competition (or Porter's externalities) has a positive effect on firm productive efficiency level, suggesting that competitive regions are more conducive to improving firm productive efficiency than oligopolistic regions. Markets with higher competition levels may provide more incentives for firms to innovate, which then leads to improvements in efficiency.

Two spatial variables related to agglomeration, urban region and industry location, also exert positive effects on firm productive efficiency. This confirms that the existence of urban regions and industry locations with stronger infrastructure and sound business environments is important for enhancing firm productive efficiency levels. Firms located in these regions tend to have greater opportunities to enjoy higher efficiency levels relative to firms locate outside urban regions or industry locations.

The findings on firm and industry characteristics also show that firm age has a positive effect on productive efficiency, indicating that older firms enjoy higher efficiency relative to younger firms, suggesting they have greater experience managing their business. In addition, the positive effect of firm size indicates that larger firms tend to have higher efficiency levels than smaller firms. Large firms have stronger market power, which helps them to achieve better efficiency levels. Finally, market concentration produces a negative effect on firm productive efficiency. This means that lower industrial concentrations or competitive market structures are better for stimulating firm efficiency than high industry concentrations or oligopolistic market structures. This is in line with the result predicted from Porter's externalities.

8.2.2. Decomposition of Productivity Growth

The decomposition analysis is performed using the Färe-Primont productivity index at the three-digit industry level to find more detailed features of productivity in each industry (Chapter 6). The results show that year-over-year trends in productivity growth fluctuate. Technical change is the main source of productivity growth, while scale efficiency change and technical efficiency change contribute less actively to productivity growth. Among the industries studied, the motor vehicle industry (ISIC 341) most frequently achieves the highest level of productivity. The results also show that TFP growth increased after the national industrial development policy was implemented in 2004, indicating that the policies exerted a beneficial influence. High-technology industries proved to be the sub-sector that most frequently experiences positive productivity growth, while low-technology and labour-intensive industries are the sub-sectors that experience low or even declining productivity growth.

8.2.3. The Effect of Agglomeration Economies on Productivity Growth

The estimation of the effect of agglomeration economies on productivity growth in Chapter 7 is performed using panel data for both static and dynamic models. In the static model, the findings show positive effects of specialization (or MAR externalities) and negative effects of diversity (or Jacobs' externalities). This is in accordance with the estimated results of agglomeration economies on firm-level productive efficiency, which supports Marshall's theory. Firms located in the more specialized regions enjoy higher productivity growth relative to the firms located in the more diversified regions. The estimated impact for competition (or Porter's externalities) is not statistically significant, so no inference can be drawn from this result.

Furthermore, the results for firm and industry characteristics show that firm age exerts a negative effect on productivity growth, in that younger firms tend to have higher productivity growth than older firms. Since younger firms can adopt new technology rapidly, it is possible to achieve higher productivity growth. Firm size also exerts a positive effect on productivity growth, meaning that larger firms tend to have higher productivity growth. The negative effect of market concentration indicates that competitive industries lead to higher productivity growth, since the competition provides incentives for firms to innovate. Finally, urban regions are also better for improving productivity growth, in that firms located in urban region experience better productivity growth than do firms located outside urban region. In brief, the estimation results of the effects of agglomeration economies on productivity growth and on firm-level productive efficiency are in agreement, as are the estimation results for the effects of firm and industry characteristics.

In addition, the empirical results for two-digit industry level show that specialization is influential in almost all sub-sectors. This also applies to other variables, namely firm size and urban region. However, other variables including diversity, competition, firm age, and market concentration have divergent effects across industries. These differences are logical, since each industry has its own structure, characteristics, and behaviours, leading to different responses to those variables.

Finally, when replacing total factor productivity (TFP) growth with real labour productivity levels, the estimation of the effects of agglomeration economies on productivity growth using a dynamic model produces similar findings. The lag of productivity has positive sign. This confirms that the productivity in the previous period contributes significantly to the current productivity, suggesting that the use of technology in the previous period plays an important role in current firms-level productivity.

One of the results that need to be considered in this study is the difference of firm age influence upon firm-level technical efficiency in Chapter 5 and productivity growth in Chapter 7, where it shows positive and negative respectively. It should be noted that, in this case, it is possible to get different results because the technical efficiency and productivity growth has different behaviour even though technical efficiency is a component of productivity. Moreover, both the data use different measurement units. Technical efficiency is measured in terms of level, which increases over time along the period of study, while the productivity growth is measured in terms of growth or difference, which tends to fluctuate over the period of study.

8.3. Policy Implications

Several potential policies implications arise on the basis of the empirical findings. Firstly, this study finds that agglomeration contributes significantly to firm level productive efficiency and productivity growth. Therefore, the Indonesian government should consider prioritizing agglomeration in formulating its spatial industrial policy, specifically by focusing on facilitating the agglomeration process and improving the competitiveness of agglomeration areas. Since the centres of agglomeration in different industries are often in the same regions, the government should consider the possibility that spatial congestion has reached a maximum level that has led to decreased economic productivity on the whole. The emergence of new agglomeration centres should be facilitated to accelerate regional development and to generate a greater mass of economic activity, which will eventually lead to productivity growth. Since the agglomeration process is also driven by the private sector through market forces, such as productivity and economies of scale, the private sector is expected to be able to utilize the government facilities to reach their optimum scale, with productivity spillovers encouraging the industrial agglomeration.

Secondly, it is noted that the level of competition in terms of region and industry sector significantly affects firm-level productive efficiency and productivity growth. This implies that the government should ensure a competitive business environment by formulating a convenient industrial policy and implementing market surveillance to curve monopoly. One of the classic problems in Indonesian manufacturing development is the existence of high market concentration in many industries. The existence of oligopolistic or monopolistic market structures with very limited numbers of players leads to inefficient allocation of resources and creates market distortion. Strengthening national bodies such as the Commission for the Supervision of Business Competition *(Komisi Pengawas Persaingan Usaha–KPPU)* could be a good solution to improve the efficiency of the market in order to encourage overall productivity.

Thirdly, the presence of industrial complexes has a positive effect on firm-level productive efficiency, so the government should pay additional attention to this program. The emergence of industrial complexes in Indonesia began with Presidential Decree 41/1996. However, the progress of development was relatively slow until the decree was strengthened by a more comprehensive formal regulation, namely Government Regulation 24/2009. The government should continue to develop industrial complexes in order to promote industrial development, as well as special economic zones and integrated economic development zones. Industrial complexes should be modernized by creating linkages with markets and academic institutions to create integrated clusters.

Fourthly, urban regions are found to promote firm productive efficiency and productivity growth, so the government should strive to ensure sound and ever improving business environments in these areas. The majority of urban regions are located around centres of agglomeration, creating buffer zones. The government should develop adequate and integrated infrastructure across regions to create higher multiplier effects from development. On the other hand, the government should also promote other potential regions to reduce the inter-regional development gap and to avoid a counterproductive "density trap."

8.4. Limitations and Focus for Future Research

The empirical results in this study provide some important insights for research on agglomeration economies and productivity growth, specifically for researchers and policy makers in Indonesia. However, this study has also some limitations that should be considered in interpreting the findings and in conducting further empirical research.

The main limitation of this study is the lack of data, which is relatively difficult to solve. Indonesian Statistics (BPS) made some reforms to the manufacturing database and survey. As a consequence, there were also some fundamental changes in the data structure and coding. Several important challenges in regard to the manufacturing database are described as follows. (1) Starting in 1998, the BPS changed the industrial classification coding from the old version to the new version, which is completely different. However, until 2003, the transformation process was not fully completed, so a lot of data are missing in this period. (2) The firm identity codes (PSID) in the years 2001 and 2002 are missing, and only preliminary coding is available, which is not complete. (3) In 2006, the survey of the manufacturing industry was conducted simultaneously with the national economic survey. As a result, some of the variables have different definitions from the manufacturing surveys conducted before and after 2006. (4) Some variables are only available in a few recent surveys, such as information about industrial location (complexes), which is only available since 2004. (5) Due to the decentralization policy that was implemented in 1999, many regional fragmentations took place after 1999. This creates challenges in the measurement of variables used in the estimation, especially those that should be measured based on region.

Furthermore, as research on agglomeration economies more generally, this is study is limited in its measurement of some variables related to agglomeration economies. The measurement of variables such as specialization (or MAR externalities), diversity (or Jacobs' externalities), and competition (or Porter's externalities) always faces constraints in the way they are measured, where they are measured, at which levels of industry, and at which levels of spatial aggregation. Since the agglomeration economies variables in this study are measured based on province and two-digit manufacturing level, this may cause aggregation bias.

Finally, this study focuses its analysis only on the period from 2000 to 2009, starting from the manufacturing industry's recovery after the severe economic crisis in 1998. This period is important because there were some important industrial policies released after 2000, and more importantly, those policies concern spatial concentration and industrial clusters, which are closely related to agglomeration economies. However, leaving out the period prior to the crisis and the crisis period itself may omit important information on agglomeration economies in those periods, which could be compared with the period of study.

Despite these limitations, this thesis provides important contributions in the empirical literature, specifically for the Indonesian case, where agglomeration is the main feature of manufacturing development and empirical studies on this subject are very limited. The methodology and the nature of this study are different from those of previous studies. The use of total factor productivity (TFP) growth as the dependent variable offers new insights to the literature. The empirical findings in this study offer valuable input for future studies and policy making in Indonesia, especially policy related to industrial agglomeration.

APPENDICES

APPENDIX to Chapter 5

Appendix 5.1: Description of Variables and Data Used in the Estimation

Variables in the model	Description	Variables name in the annual manufacturing survey		Remarks
Y	Output	OUTPUT	Goods produced (YPRVCU)	Total value of firms' output
			Manufacturing services received (YISVCU)	
			Other revenues (YRNVCU)	
			Stock of semi-finished products (end–beginning of year) (SHFVCU)	
			Electricity sold to others (YELVCU)	
K	Capital	V1115 (Fixed)	Land (V1101)	Estimated value of all fixed capital based on current value per 31 December.
			Building (V1103)	
			Machinery and equipment (V1106)	
			Vehicles (V1109)	
			Others (V1112)	
		SRMVCU (Stock)	Stock of raw materials, fuel, packaging, and other materials	Value of stock at the end of the year – value at the beginning of the year.
L	Labour	LTLNOU	Number of production workers male and female (LPRNOU)	Total number of workers includes production and non-production workers.
			Number of other workers male and female (LNPNOU)	

Variables in the model	Description	Variables name in the annual manufacturing survey		Remarks
M	Material	RTLVCU	Domestically produced (RDNVCU)	Materials used during the year, for domestically produced and imported goods.
			Imported (RIMVCU)	
E	Energy	EFUVCU	Gasoline (EPEVCU)	Total value of fuel and lubricants used during the year
			Diesel fuel/HSD/ADO (ESOVCU)	
			Kerosene (EOIVCU)	
			Coal (ECLVCU)	
			Public Gas (EGAVCU)	
			LPG (ELPVCU)	
			Others fuels (ENCVCU)	
			Lubricant (ELUVCU)	
		EPLVCU	Electricity purchased from PLN (EPLVCU)	Total value of electricity used during the year
		ENPVCU	Electricity purchased from non-PLN (ENPVCU)	
LQ	Specialization index	-	Calculated based on total number of workers, both production and non-production (LTLNOU);	
DIV	Diversity index	-	Calculated based on total number of workers, both production and non-production (LTLNOU);	
COM	Competition index	-	Calculated based on total number of workers, both production and non-production (LTLNOU); number of firms in each industry (NFIRM).	The measurement is as mentioned in sub-section 5.3.2.
AGE	Firms age	-	The age of firm, this is calculated from the time at which the firm was established.	

Variables in the model	Description	Variables name in the annual manufacturing survey		Remarks
SIZE	Firm size	-	Total number of workers, both production and non-production (LTLNOU)	
CR4	Industrial concentration	-	Value added share of four largest firms based on 2-digit ISIC level.	
DURB	Urban area	-	Dummy variable for urban areas/regions selected from the third-tier of regional government (regency or city) that provide substantial contribution to the manufacturing industry.	
DLOC	Industrial area/complex	LOCATI	Dummy variable for industrial area/complex	

Source: Large and Medium Industrial Statistics 2009, Statistics Indonesia *(Badan Pusat Statistik – BPS)*.

Data of Price Indexes

Types of Data	Description	Sources
Wholesale Price Index (WPI)	WPI of the manufacturing industries which are available at 4-digit ISIC for deflating value of output, capital, value-added, materials, and goods production.	Statistics Indonesia *(Badan Pusat Statistik – BPS),* and CEIC Database
Wholesale Electricity Index (WEI)	WEI of electricity produced by State Electricity Company and Private Company for deflating value of electricity.	State electricity company (*Perusahaan Listrik Negara – PLN)*
Fuels Price Index (FPI)	FPI for deflating the value of fuels expenditures	Statistics Indonesia *(Badan Pusat Statistik – BPS)*

Appendix 5.2: Data Cleaning Procedure

As explained previously, the data used in this study are medium-large manufacturing firms provided by the Statistics Indonesia *(Badan Pusat Statistik – BPS)* from 2004 to 2009. This study uses the balanced panel data set for the estimation of translog production frontier and the effects of agglomeration economies on total factor productivity (TFP) growth. To develop the balance panel data set, we need to run data cleaning procedure because many structural inconsistencies are founded in the medium-large manufacturing data published by BPS. BPS has made various modifications and adjustments in the surveyed industries including the updating of the classification code, variable definitions, survey coverage and sectoral adjustment. Inconsistencies in the data are also found in the value of variables due to an error in filling out the questionnaire and error in the data entry process. Following the method applied by Margono and Sharma (2006), Ikhsan (2007) and Suyanto et al. (2009), the data cleaning procedure in this study can be described as follows:

Step 1: adjustment the code of companies (PSID)

To obtain the same observations, for each year of the balanced panel, the first step to be taken is to adjust the companies data based on their codes. BPS consistently provides company's code or reference in annual manufacturing survey, namely PSID. Based on the PSID code, the manufacturing data from 2004 to 2009 are synchronized to get the balanced panel data set. So that the companies (establishments) used as sample in this research are the companies with the same PSID code over the period 2004 to 2009. As consequence, the firm entry and exit factor is not included in this study. The firm that established after 2004 are dropped from the sample set.

Step 2: adjustment of variables definition

The second step is to adjust the variables definition used in the estimation model. Various differences on the name of variables are founded in the annual manufacturing survey published by the Indonesian Statistics. As consequence, it should be adjusted to obtain a consistent data set. Appendix 5.1 outlines the definition of variables used in this study based on the questionnaire of annual manufacturing survey conducted by the Indonesian Statistics.

Step 3: cleaning for noise and typographical errors.

To minimize noise and typographical errors, this study follows several steps:

a. Firms with zero values for output, labour, raw material and energy are dropped from the sample set.
b. Firms with missing value for output, labour, raw material and energy are also dropped from the sample set.
c. The missing value of the data in this empirical analysis is dropped from the sample set.
d. The final dataset for period 2004 to 2009 is consisting of 4,240 firms each year with total observations are 25,440 firms. The number of sample by industries is presented in the following table (Appendix 5.3).

Appendix 5.3: Number of Observations per year, by Industry in 2-digit ISIC, 2004-2009

ISIC	Industries	Samples
15	Food products and beverages	1,277
16	Tobacco	144
17	Textiles	343
18	Wearing apparel	175
19	Tanning and dressing of leather	103
20	Wood and products of wood except furniture and plating materials	202
21	Paper and paper products	92
22	Publishing, printing and reproduction of recorded media	121
23	Coal, refined petroleum products and nuclear fuel	8
24	Chemicals and chemical products	264
25	Rubber and plastics products	316
26	Other non-metallic mineral products	497
27	Basic metals	30
28	Fabricated metal products, except machinery and equipment	118
29	Machinery and equipment n.e.c	35
31	Electrical machinery and apparatus n.e.c	43
32	Radio, television and communication equipment and apparatus	11
33	Medical, precision and optical instruments, watches and clocks	8
34	Motor vehicles, trailers and semi-trailers	50
35	Other transport equipment	32
36	Furniture and manufacturing n.e.c	364
37	Recycling	7
	Total observations per year	**4,240**

Source: Large and Medium Industrial Statistics, Statistics Indonesia *(Badan Pusat Statistik – BPS)*, author's calculation.

Appendix 5.4: Summary Statistics of the Variables

Variable	Mean	SD	Min	Max
LnY	15.057	2.177	9.371	23.687
LnL	4.474	1.247	2.996	10.618
LnK	13.452	2.623	0.166	29.921
LnM	14.165	2.422	5.737	22.704
LnE	11.667	2.229	3.360	20.853
T (time)	3.500	1.708	1.000	6.000
LQ (specialization)	0.942	0.198	0.278	2.449
DIV (diversity)	7.663	2.011	1.106	10.111
COM (competition)	1.012	0.128	0.322	2.265
AGE	20.203	12.602	1.000	103.000
SIZE	4.474	1.247	2.996	10.618
CR4	27.074	15.064	9.290	93.490
DURB	0.465	0.499	0.000	1.000
DLOC	0.089	0.285	0.000	1.000

Notes: all variables in production frontiers (output, labour, capital, raw materials and energy) are in natural logarithm (Ln); LQ (specialization), DIV (diversity) and COM (competition) are indexes; AGE is in year; SIZE is natural logarithm of total employee; CR4 is in percentage; DURB and DLOC are dummy variables (0,1).

APPENDIX to Chapter 6

Appendix 6.1: TFP Change and Efficiency Change 2000 to 2009

Year	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale efficiency change (dISE)	Mix-efficiency change (dIME)	Residual efficiency change (dRISE)	Scale-mix efficiency change (dISME)	Residual-mix efficiency (dRME)
	(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)	(6)	(7)	(8)	(9)
2000/2001	0.9972	0.9973	0.9999	0.9903	1.0191	1.0153	0.9945	1.0097	0.9907
2002	1.0012	0.9947	1.0065	1.0126	1.0048	0.9743	1.0202	0.9940	0.9893
2003	0.9998	0.9875	1.0125	0.9998	0.9859	1.0287	0.9844	1.0127	1.0272
2004	1.0075	0.9831	1.0249	1.0153	1.0203	0.9883	1.0214	1.0095	0.9894
2005	0.9987	1.0289	0.9706	0.9944	1.0043	0.9847	0.9913	0.9761	0.9719
2006	0.9997	0.9992	1.0006	0.9845	0.9990	1.0102	1.0061	1.0163	1.0174
2007	0.9997	0.9852	1.0148	0.9995	0.9682	1.0134	1.0018	1.0152	1.0486
2008	0.9968	1.0004	0.9964	1.0077	1.0091	0.9924	0.9964	0.9888	0.9799
2009	1.0207	1.0616	0.9615	0.9937	0.9976	1.0084	0.9594	0.9675	0.9699
2000-2004	1.0057	0.9630	1.0444	1.0179	1.0301	1.0058	1.0202	1.0260	0.9960
2005-2009	1.0169	1.0454	0.9727	0.9854	0.9737	1.0245	0.9635	0.9871	1.0138
2000-2009	1.0213	1.0358	0.9860	0.9974	1.0073	1.0146	0.9744	0.9886	0.9814

Source: Author’s calculation using DPIN version 3.0.

Appendix 6.2: TFP Change and Efficiency Change by 3-digit ISIC 2000 to 2009

KLUI (ISIC)	Industry	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)	Rank dTFP
		(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)	(6)
322	Communication equipment	1.1463	1.0358	1.1067	1.0581	1.0460	1
319	Other electrical equipment	1.1038	1.0358	1.0656	1.0765	0.9900	2
300	Office accounting and data processing machinery and equipment	1.0813	1.0358	1.0439	1.0000	1.0439	3
342	Motor vehicle bodies	1.0688	1.0358	1.0318	0.9875	1.0448	4
222	Printing and activities related printing	1.0595	1.0358	1.0228	1.0301	0.9928	5
242	Other chemicals	1.0538	1.0358	1.0174	1.0432	0.9754	6
269	Other non-metallic mineral products	1.0515	1.0358	1.0152	1.0482	0.9684	7
323	Radio, television, sound and picture recordings and other similar activities	1.0495	1.0358	1.0131	1.0260	0.9875	8
201	Sawing and preserving of wood	1.0494	1.0358	1.0132	1.0289	0.9847	9
371	Recycling of metals	1.0477	1.0358	1.0115	1.0943	0.9243	10
292	Special purpose machinery	1.0462	1.0358	1.0101	1.0378	0.9733	11
273	Metal smelting	1.0429	1.0358	1.0068	1.0456	0.9629	12
264	Cement, lime plaster and gypsum	1.0423	1.0358	1.0063	0.9841	1.0225	13
241	Industrial chemicals	1.0379	1.0358	1.0020	0.9874	1.0149	14
351	Construction and repair of ships and boats	1.0379	1.0358	1.0020	0.9923	1.0098	15
173	Knitting	1.0372	1.0358	1.0014	0.9998	1.0015	16
151	Processing and preserving of meat, fish, fruits, vegetables, cooking oil and fat	1.0371	1.0358	1.0012	1.0000	1.0012	17
153	Grain mill products, flour and animal feed	1.0365	1.0358	1.0007	1.0145	0.9864	18

KLUI (ISIC)	Industry	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)	Rank dTFP
		(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)	(6)
271	Basic iron and steel	1.0360	1.0358	1.0002	1.0069	0.9932	19
333	Clocks, watches and other similar products	1.0355	1.0358	0.9996	1.0768	0.9283	20
154	Other food	1.0330	1.0358	0.9973	1.0156	0.9820	21
171	Spinning, weaving and finishing textiles	1.0330	1.0358	0.9973	0.9769	1.0208	22
192	Footwear	1.0326	1.0358	0.9968	0.9825	1.0146	23
174	Kapok	1.0315	1.0358	0.9958	0.9344	1.0656	24
251	Rubber and goods made from rubber	1.0284	1.0358	0.9928	1.0275	0.9664	25
262	Goods made from porcelain	1.0280	1.0358	0.9925	0.9488	1.0461	26
210	Paper and paper products	1.0245	1.0358	0.9890	0.9889	1.0002	27
313	Electrical cables and telephones	1.0235	1.0358	0.9881	1.0308	0.9586	28
263	Clay products	1.0225	1.0358	0.9872	0.8785	1.1236	29
312	Electrical control and distribution equipment	1.0224	1.0358	0.9871	1.0522	0.9382	30
231	Goods made from coal	1.0220	1.0358	0.9866	1.0309	0.9570	31
311	Electrical motors, generators and transformers	1.0215	1.0358	0.9862	0.9685	1.0184	32
243	Synthetic fibres	1.0186	1.0358	0.9834	1.0000	0.9834	33
272	Basic metals, except iron and steel	1.0184	1.0358	0.9832	1.0695	0.9193	34
289	Other metal products and services of metallic product processing	1.0165	1.0358	0.9813	1.0124	0.9692	35
341	Motor vehicles	1.0142	1.0358	0.9791	1.0000	0.9791	36
291	General purpose machinery	1.0142	1.0358	0.9790	0.9611	1.0186	37
172	Garments and carpets	1.0141	1.0358	0.9791	0.9487	1.0319	38
181	clothing apparel, except clothing apparels made of fur	1.0136	1.0358	0.9786	1.0125	0.9665	39
252	Plastic products	1.0133	1.0358	0.9783	1.0017	0.9766	40

KLUI (ISIC)	Industry	TFP change (dTFP)	Technical change (dTech or dTFP*)	Efficiency change (dTFPE)	Technical efficiency change (dITE)	Scale-mix efficiency change (dISME)	Rank dTFP
		(1)=(2)*(3)	(2)	(3)=(4)*(5)	(4)	(5)	(6)
191	Leather and goods made from leather	1.0122	1.0358	0.9773	0.9818	0.9955	41
202	Goods made from wood and plaints	1.0101	1.0358	0.9752	0.9573	1.0187	42
361	Furniture	1.0100	1.0358	0.9751	1.0052	0.9701	43
281	Fabricated structural metal products, tanks and pressure vessels	1.0076	1.0358	0.9727	1.0004	0.9723	44
359	Other transport equipment	1.0074	1.0358	0.9726	1.0000	0.9726	45
155	Beverages	1.0059	1.0358	0.9711	0.9967	0.9743	46
160	Processed tobacco	1.0045	1.0358	0.9697	1.0000	0.9697	47
343	Equipment and components of motor vehicles	0.9999	1.0358	0.9653	1.0377	0.9302	48
315	Bulbs, spotlights and other lighting	0.9976	1.0358	0.9631	0.9863	0.9765	49
221	Publishing	0.9952	1.0358	0.9608	0.9570	1.0039	50
331	Medical, measuring, testing and other equipment except optical equipments	0.9950	1.0358	0.9605	0.9417	1.0199	51
369	Other processing	0.9905	1.0358	0.9562	1.0190	0.9382	52
265	Goods made from stone	0.9861	1.0358	0.9520	0.9323	1.0212	53
261	Glass and goods made from glass	0.9838	1.0358	0.9498	0.9179	1.0348	54
152	Milk and food made from milk	0.9838	1.0358	0.9497	1.0011	0.9487	55
321	Electronic tubes and valves and other electronic components	0.9750	1.0358	0.9413	0.9753	0.9652	56
293	Non-classified household equipment	0.9529	1.0358	0.9200	0.9984	0.9213	57
266	Goods made from asbestos	0.9268	1.0358	0.8947	0.8920	1.0030	58
314	Electrical accumulators and batteries	0.9046	1.0358	0.8732	0.9236	0.9455	59

Source: Author’s calculation using DPIN version 3.0.

APPENDIX to Chapter 7

Appendix 7.1: Estimation of Firm-level Total Factor Productivity (TFP)

Total factor productivity growth in this chapter is calculated using the Färe-Primont productivity index measurement proposed by O'Donnell (2010, 2012). This approach is adapted from the estimation of Shepard (1953) output distance functions and associated measures of productivity change. O'Donnell (2012) states that the decomposition of productivity change can be explained by considering two aspects: choice of production technology and the transitive productivity index. The first step is choosing among the production technologies available to firms; O'Donnell (2012) follows Fernandez et al. (2000) in assuming that the production technology available to firms in period t can be represented by the separable transformation function below:

$$T^t(x,q)=g(q)-f^t(x)\leq 0 \tag{A7.1}$$

where $x=(x_1,\ldots x_k)'\in R^K_+$ and $q=(qx_1,\ldots q_k)'\in R^J_+$ denote vectors of inputs and outputs quantities. O'Donnell (2012) explains that the Shepard (1953) output and input distance functions are alternative representations of this production technology.

$$D^t_0(x,q)=min_\delta\{\delta>0:T^t(x,\tfrac{q}{\delta})\leq 0\} \tag{A7.2}$$

and

$$D^t_I(x,q)=max_\delta\{\rho>0:T^t(x,\tfrac{q}{\rho})\leq 0\} \tag{A7.3}$$

The output distance function provides the inverse of the largest factor by which a firm can increase its output vector while holding the input vector fixed. Meanwhile, the input distance function gives the maximum factor by which a firm can decrease its input vector and continue producing the same output vector. O'Donnell (2012) mentions that if the technology exhibits constant returns to scale, then $D^t_o(x,q)=D^t_I(x,q)=1$, so that technically-feasible and efficient input-output combinations are defined by $T^t(x,q)=0$ and $D^t_0(x,q)=D^t_I(x,q)=1$. A local measure of returns to scale is the elasticity of scale, which can be defined as:

$$\eta(x,q,t)\equiv-\left[\sum_{k=1}^{K}\frac{\vartheta T^t(x,q)}{\vartheta x_k}x_k\right]\bigg/\left[\sum_{j=1}^{J}\frac{\vartheta T^t(x,q)}{\vartheta q_j}\right]^{1} \tag{A7.4}$$

The technology exhibits (local) decreasing, constant, or increasing returns to scale when the elasticity of scale is less than, equal to, or greater than one. The transformation function in Equation A7.1 is assumed to satisfy standard regularity conditions, such as:

Non-decreasing in outputs: $T^t(x,q^1) \geq T^t(x,q^0) \, for \; q^1 \geq q^0$ (A7.5)

Non-increasing in inputs: $T^t(x^1,q) \geq T^t(x^0,q) \, for \; x^1 \geq x^0$ (A7.6)

Furthermore, the output distance function has the following properties:

Non-increasing in inputs: $D_0^t(x^1,q) \leq D_o^t(x^0,q) \, for \; x^1 \geq x^0$ (A7.7)

Non-decreasing in outputs: $D_0^t(x,q^1) \leq D_o^t(x,q^0) \; for \; q^1 \geq q^0$ (A7.8)

Linearly homogenous in outputs: $D_0^t(x,\lambda q) \equiv \lambda D_0^t(x,q) \, for \; \lambda > 0$ (A7.9)

From Equation A7.1, it is convenient to let:

$ln\,(q) = \theta^{-1} ln\left(\sum_{j=1}^{J} \alpha_j^\theta q_j^\theta\right) + v$ and (A7.10)

$ln f^t(x) = \gamma_0 + \gamma_1 t + \sum_{k=1}^{K} \beta_k \, ln x_k + \varepsilon$ (A7.11)

where $\boldsymbol{\varepsilon}$ and v are error approximations. O'Donnell (2012) further explains that the regularity properties in Equation A7.7 to A7.9 will be satisfied if:

$\theta > 1,$ (A7.12)

$\alpha_j \in (0,1) \; for \; j=1,\ldots,J,$ (A7.13)

$\beta_k \geq 0 \; for \; k=1,\ldots K$ and (A7.14)

$\alpha' \iota_j = 1$ (A7.15)

where $\alpha = (\alpha_1,\ldots,\alpha_J)'$ and ι_J is a $Jx1$ unit vector. Equation A7.10 is a constant elasticity of substitution (CES) function, with elasticity of transformation between any two outputs equal to $1/1(1-\theta) < 0$. Equation A7.11 is a Cobb-Douglas (CD) function that allows for Hicks-neutral technical change. The logarithms of the output and input distance functions can be derived from Equation A7.1, A7.10, and A7.11 as follows:

$$ln\, D_0^t(x,q) = \theta^{-1} ln\left(\sum_{j=1}^{J} \alpha_j^\theta q_j^\theta\right) - \gamma_0 - \gamma_1 t - \sum_{k=1}^{K} \beta_k ln x_k + v \quad \text{(A7.16)}$$

$$ln\, D_I^t(x,q) = \eta^{-1}\left[\gamma_0 + \gamma_1 t + \sum_{k=1}^{K} \beta_k \, ln\, x_k - \theta^{-1} \, ln\left(\sum_{j=1}^{J} \alpha_j^\theta q_j^\theta\right) + \varepsilon\right] \quad \text{(A7.17)}$$

where $\eta = \sum_k \beta_k$ is the elasticity of scale. O'Donnell (2012) shows that the estimation of the parameters of these distance functions can be used to estimate a spatially- and temporally-transitive index of productivity change. In addition, Equation A7.16 and A7.17 can be written as:

$$ln\, D_0(x,q,t) = ln\, g(q) - ln\, A(t) - ln\, f(x) \quad \text{(A7.18)}$$

$$ln\, D_I(x,q,t) = \eta^{-1}\left[ln\, A(t) + ln\, f(x) - ln\, g(q)\right] \quad \text{(A7.19)}$$

where $g(q)$ is linearly homogeneous and $f(x)$ is homogeneous at degree r. From Equation A7.18 and A7.19, the Färe-Primont index to decompose productivity change can be written (O'Donnell 2011):

$$TFP_{ms,nt} = \left(\frac{A(t)}{A(s)}\right)\left(\frac{g(q_{nt})}{A(t)f(x_{nt})}\frac{A(s)f(x_{ms})}{g(q_{ms})}\right)\left(\frac{f(x_{ms})}{f(x_{nt})}\right)^{(1-\eta)/\eta} \quad \text{(A7.20)}$$

where TFP_{ms} denotes the TFP of firm m in period s and TFP_{nt} is the TFP of firm n in period s. From Equation A7.20, the first component in the right hand side represents the technical change or technical progress, the second component is output technical efficiency change, and the third component is scale efficiency change. If there is no technical inefficiency and the technology exhibits constant return to scale (CRS) the index collapses to the "Solow residual" (O'Donnell 2012)[26].

The reason for applying this method in this study is that this is the most recent approach to the decomposition of productivity change developed by O'Donnell (2012). In Indonesia's case, there are no previous studies that apply this method. There is an opportunity therefore to apply it and compare the results of the decomposition of productivity change with other methods. Accordingly, the TFP index numbers method matches the principle of multiplicative completeness (O'Donnell 2012). The third reason is that this approach can be solved without requiring specific computer programs.

[26] The decomposition of productivity change in Equation A7.20 can be performed in a computer program such as Microsoft Excel once the scale elasticity (η) and technology (A) are obtained from the estimation. The scale elasticity (η) and A can be estimated by using computer program such as Frontier 4.1. The decomposition of productivity change can be easily performed using the software package DPIN 3.0 developed by O'Donnell (2011). However, this software limits the number of observations to a maximum of five thousand. Since there are 45,116 observations in this study, the calculation of TFP change was performed manually using Microsoft Excel. The detail method and decomposition technique can be found in the Course Module of Applied Productivity and Efficiency Analysis provided by the Centre for Efficiency and Productivity Analysis (CEPA) of the School of Economics, The University of Queensland.

Appendix 7.2: Estimation Procedure for the Missing Value of Capital

The measurement of capital is more challenging than that of other production inputs such as labour and materials. Coelli et al. (2005) argue that the main reason for the difficulty of the treatment of capital is that it is a durable input. In contrast to labour and materials, which are utilised in one accounting period of production, capital assets are purchased in one period and used in the production process for the course of their life, until new assets replace them. Due to the complexity of the measurement, there are a large number of missing capital values in the data. To obtain the proxy number for the missing capital values, this study uses replacement values for fixed assets, following Vial (2006), Ikhsan (2007), and Suyanto et al. (2009). The missing capital value for the period from 2000 to 2009 is estimated by the back-casting method, as explained in the following equation:

$$lnK_{it}=\beta_0+\beta_1 lnY_{it-1}+\mu_{it}+v_{it} \quad \text{(A7.21)}$$

where K_{it} represents the fixed assets of firm i at time t, Y_{it-1} is the lagged output of firm i at time $t-1$, μ_{it} is the unobservable individual effect, and v_{it} is disturbance. Following Vial (2006), the above equation is estimated using random effects Generalised Least Square (GLS) panel regression. Random effects are employed because there are a large number of observations in this estimation, so using the fixed effects model would lead to the loss of a significant number of degrees of freedom (Greene 2003). Moreover, the random effect approach is preferred for a panel set of data with relatively more samples than times periods (Baltagi 2008).

The estimation result from the random effect GLS is shown in the following table. It shows an expected result in which the coefficient of Y_{it-1} and the constant variable are positive and significant at the one percent level, but the diagnostic tests for the dependent variable (lnK_{it}) and independent variable (lnY_{it-1}) indicate a high serial correlation. The serial correlation test is performed by applying the Wooldridge test for autocorrelation to the panel data.

The Random Effects GLS Estimates of Capital and the One-year Lag of Output (dependent variable is lnK_{it})

variable	coefficient	standard error	z-statistic	P>|z|
constant	0.3523	0.0488	72.09	0.000
lnY_{it-1}	8.6188	0.0741	116.23	0.000
R^2 within	0.0066			
R^2 between	0.4338			
R^2 overall	0.1160			

Source: Author's calculation.

To overcome the serial correlation problem and to ensure homoscedasticity, Equation (A7.1) is re-estimated using the Random Effects Feasible GLS, as proposed by Baltagi and Wu (1999). The procedure for this estimation is to add first-order autoregressive (AR1) to the residual structure, so that the residual in equation (A7.1) becomes $v_{it}=\rho v_{it}+\omega_{it}$, where $-1<\rho<1$ and $\omega_{it}\sim iid(0,\sigma^2_{\omega})$. The estimation results from the Feasible GLS approach are shown in the following table. The Baltagi-Wu LBI value indicates that no serial correlation exists. Based on this estimation, the value of capital is predicted and then used to replace all the missing values of capital.

The Random Effect Feasible GLS Estimates of Capital and the One-Year Lag of Output (dependent variable is lnK_{it})[27]

variable	coefficient	standard error	z-statistic	P>|z|
Constant	0.2079	0.0050	41.24	0.000
lnY_{it-1}	10.7407	0.7674	139.95	0.000
R^2 within	0.0066			
R^2 between	0.4338			
R^2 overall	0.1160			
Modified Bharvaga Durbin-Watson	1.5798			
Baltagi-Wu LBI	1.9815			

Source: Author's calculation

[27]) All the estimation procedures are performed using Stata version 12.1. The commands used for random effects GLS, serial correlation test, random effects FGLS, and prediction of capital are *xtreg, xtserial, xtregar*, and *predict*, respectively.

Appendix 7.3:

Estimation Results of Panel Data using AR1, Dependent Variable:
Total Factor Productivity (TFP) Growth, 2001–2009

Independent variables	Fixed-effect with $\varepsilon_{i,t-1}$
	(1)
LQ *(specialization)*	26.765
	(15.16)[a)]
DIV *(diversity)*	-5.613
	(-22.53)[a)]
COM *(competition)*	3.693
	(1.49)
AGE *(firm's age)*	-0.232
	(-6.66)[a)]
SIZE *(firm's size)*	30.640
	(91.30)[a)]
CR4 *(concentration)*	-0.587
	(-15.26)[a)]
DURB *(dummy urban)*	24.156
	(28.68)[a)]
Constanta	-93.174
	(-26.07)[a)]
N	4,516
Observations	40,644
R^2	0.1624
Modified Bhagarva et al. DW	2.0430
Baltagi-Wu LBI	2.1392

Note: t-statistics are in parentheses; [a]), [b]), and [c]) denote 1%, 5%, and 10% significance level, respectively.

Appendix 7.4: Estimation of the Dynamic Model Using TFP Growth as the Dependent Variable, 2001-2009

For the purpose of discussion, this appendix presents the estimation of the dynamic panel model, in which the dependent variable is total factor productivity (TFP) growth. As discussed in sub-section 7.6.5, the use of TFP growth as a dependent variable in the dynamic model cannot provide expected estimation results in line with the nature of agglomeration economies. Applying a dynamic panel model such as GMM-SYS requires first-difference variable measurements, because the estimation of GMM-SYS uses a first-difference model. As mentioned in Cameroon and Trivedi (2010), the basic estimation model of GMM-SYS is written as:

$$\Delta y_{it}=\gamma_1\Delta y_{i,t-1}+\ldots+\gamma_p\Delta y_{i,t-p}+\Delta x_{it}^{'}\beta+\Delta\varepsilon_{it}\ ,t=p+1,\ldots,T \qquad \text{(A7.22)}$$

Since the value of total factor productivity (TFP) growth is already in difference form, using this variable as the dependent variable causes complications in the data measurement, because the estimation then deals with the variable in the form of a difference of the first-difference.

The following table shows the estimation results. The main concern is the lag of total factor productivity growth, or TFP(-1), which has a negative effect on productivity growth. Conceptually, the productivity lag is expected to provide positive effects on current productivity, since there is a technological adjustment between the previous period and current period. For that reason, following previous studies such as Henderson (2003), Kuncoro (2009), and Andersoon and Lööf (2011), the estimation of the dynamic model in sub-section 7.6.5 uses real labour productivity to represent the firm productivity level, rather than total factor productivity (TFP) growth.

Estimation Results of Dynamic Model, Dependent Variable: Total Factor Productivity (TFP) Growth 2001–2009

Independent variables	Pooled OLS (1)	FEM (2)	GMM-SYS (3)
TFP growth (-1)	-0.336	-0.382	-0.325
	(-64.94) a)	(-161.73) a)	(-55.34) a)
LQ *(specialization)*	7.898	21.966	32.874
	(5.58) a)	(10.30) a)	(5.83) a)
DIV *(diversity)*	-2.342	-5.496	-9.354
	(-17.40) a)	(-19.27) a)	(-15.31) a)
COM *(competition)*	6.631	12.738	3.986
	(3.17) a)	(4.72) a)	(0.76)
AGE *(firm's age)*	-0.215	-0.378	-0.494
	(-10.67) a)	(-8.20) a)	(-6.13) a)
SIZE *(firm's size)*	19.054	33.070	11.681
	(56.46) a)	(67.66) a)	(13.51) a)
CR4 *(concentration)*	-0.091	-0.742	-1.391
	(-6.45) a)	(-19.42) a)	(-27.74) a)
DURB *(dummy urban)*	10.313	24.853	51.025
	(20.73) a)	(23.87) a)	(25.71) a)
Constanta	-56.609	-100.368	47.997
	(-20.29) a)	(-23.68) a)	(6.36) a)
AR(1)			-20.81
			(0.000)
AR(2)			-0.97
			(0.329)
Instrumental variables			105
Observations	36,128	36,128	31,612

Note: t-statistics are in parentheses; a), b), and c) denote 1%, 5%, and 10% significance level, respectively.

Above table shows the estimation results. The main concern is on the lag of productivity growth or TFP(-1), which has negative effects on productivity growth. Conceptually, the lag of productivity is expected to provide positive effects on current productivity, since there is a technological adjustment between the previous period and current period. For that reason, following previous studies such as Henderson (2003), Kuncoro (2009), and Andersoon and Lööf (2011), the estimation of dynamic panel in the sub-section 7.6.5 uses real labour productivity to represent firm productivity instead of total factor productivity (TFP) growth.

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